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Open and Collaborative Climate Change Mitigation Planning for Electric Power Grids

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By

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Abstract

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Global warming is one of the most significant problems facing humanity, and reducing emissions from the electricity sector is critical for mitigating global warming impacts. My work here focuses on developing computational tools to plan cost effective mitigation pathways for the electricity sector and using them collaboratively. The complexity and scale of globally transitioning electrical power grids away from fossil fuels over the coming decades will require a large-scale collaborative effort with effective coordination of many actors trained in diverse disciplines. Historically, energy-modeling efforts have tended to be siloed and fragmented between and even within research groups. In my research I have attempted to provide an alternative to that status quo by improving an open source renewable planning model, Switch, increasing its usability and accessibility to interdisciplinary researchers, and collaboratively applying it to mitigation planning.

We used the Switch model to conduct detailed research into cost effective mitigation pathways for the Western portion of North America, or the WECC power grid. We found that renewable portfolio standards were insufficient to meet climate stabilization goals, and more targeted policies were needed that specifically focused on emission reductions. We identified investment plans that could lead to dramatic decreases in emissions without significantly increasing electricity costs over the next twenty years by retiring coal and replacing it with natural gas and renewables while evolving the grid to better accommodate variable renewable energy.

We found that meeting overall 2050 targets will require concerted action on many fronts, including aggressive efficiency programs, electrification of transportation and heating, and dramatically reducing emissions from the electricity sector. Meeting 2050 emission goals without significantly increasing energy costs also will require additional technological innovation. Two promising technological pathways for long-term cost containment are developing low cost solar in conjunction with low cost storage or demand response, and developing Biomass Energy with Carbon Capture and Sequestration (BECCS) to provide emission offsets during the last stages of emission

reductions. We found that the emissions offsets provided by BECCS were much more valuable than the energy, suggesting that other sequestration options such as improved land management that increases soil carbon deposition could be a particularly valuable part of an economy-wide portfolio.

We started this research in the early days of the natural gas boom caused by widespread use of hydraulic fracturing. As data emerged on potentially high methane leakage rates in the natural gas supply chain, we investigated how leakage impacts roles Natural Gas (NG) can play in a low emission power grid. We found that leakage rates significantly reduce the use of NG as a direct substitute for coal, but have a smaller impact on the use of combustion turbines for reserves and peaking capacity. Higher leakage rates increase electricity costs in optimal solutions by an average of 1.3% ±0.068 and decrease NG consumption by 18% ±0.55 for each percentage point increase in the leakage rate in the next decade.

Increased leakage can increase or decrease the use of NG to complement renewables, depending on the emissions cap context and technological alternatives. In the 2020 and 2030 timeframes under moderate emission caps, higher leakage rates prompt the installation of more renewables and prompt NG Combined Cycle Gas Turbines (CCGT) to shift from baseload operation to running as-needed to complement renewables. In the 2030 timeframe, higher leakage often prompts installation of new NG Combustion turbines with Compressed Air Energy Storage, which is used to complement variability from renewable resources within a day. Scenarios that include low-cost battery storage or low-emission baseload options of Coal CCS or Nuclear have less Compressed Air Energy Storage installed in the 2030 timeframe because these technologies provide alternate emission reduction paths. In the 2040 and 2050 timeframes with tighter emission caps, NG is already used primarily to complement renewables and higher leakage rates tend to decrease its use in any role.

Throughout this process, I made significant advancements to Switch as an analytical tool for collaborative work by interdisciplinary research teams. I initially increased the usability and lowered the learning curve while training colleagues who lacked computer science backgrounds, as well as developing execution workflows to increase reproducibility and leverage high performance workstations and computing clusters. I played a crucial role in developing detailed databases to describe the WECC electricity grid and calculating renewable energy potential at a high geographic and temporal resolution over a large area. I developed new techniques for describing policies and tracking both the renewable fraction and emission intensity of electricity. I developed techniques for simulating grid dispatch of investment portfolios on ~100x as many timepoints to better estimate reliability, costs and emissions. I used that instrumentation ability to improve sampling methods and solution quality. Interviews with current and potential users indicated a need for a completely open source software stack, streamlined workflows for data ingestions and processing, as well as a graphical front-end to complement the command line interface. These usability enhancements are the subject of ongoing and future work.

Overall, this open collaborative approach has proven quite successful. We trained four other research teams on two campuses to develop versions of this model for China, Chile and Nicaragua and to conduct a detailed systems-level analysis of Carbon Capture and Sequestration technologies. Those efforts led to recognition by the United Nations during the 2014 Climate Summit. We have developed partnerships with a second academic campus, a consulting firm and Google who are all contributing to a new implementation of Switch in a completely open source software stack that supports stochastic programming and decomposition (Pyomo). We hope that the new version can serve as a open platform for evaluating and comparing research methodologies as well as supporting investment planning and policy analysis for consulting firms, government agencies, academics, utilities and NGOs.

To Kate, for all of your encouragement, support and love.

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Preface

Electricity decarbonization is an extremely complex and important problem whose solution requires the coordinated efforts of many people. Effective contributions to this field require understanding and fitting into the larger social process of research, planning and implementation rather than working as an individual in relative isolation. Historically, most communication and coordination within academia has been mediated through journal publications, conferences and occasional exchanges of digital data. Many research contributions to this field have been based on individual researchers implementing analytic tools from descriptions in the literature. Individual researchers often reuse and extend their own work, but it is less common for these tools and models to be used by a larger research lab, or to be shared or reused by other research groups. This trend is in contrast to an open source strategy of preferentially reusing and extending prior work, and only implementing new work when necessary.

My approach throughout my doctoral work has been to embrace the collaborative social process of science. This may have been easier for me than most because prior to graduate school, I worked in a computational biotech lab and learned to embrace open source culture and strategies. Part of this meant removing my ego attachment to "I wrote this entirely by myself", and instead considering how I can most effectively contribute to larger goals and broader society. Near the beginning of my doctorate, I learned of a cutting-edge investment-planning model (Switch) that had been written by a graduating doctoral student. Switch was open source and had dramatically new functionality that was not offered by other energy planning models at that time; namely incorporating renewable integration requirements into grid investment optimization. Most studies at the time examined how renewables could be integrated on a marginal basis into a legacy grid, rather than looking forward to what kind of grid we could build to accommodate large shares of renewables.

I joined a team of students that extended Switch to add new functionality, increase usability and expand geographic scope. I made significant contributions to modeling, training, implementing new features, analysis and providing all manner of computational support. We used Switch and other tools to develop decarbonization pathways for California and the western portion of North America and to conduct more targeted studies examining systems impacts of select technological advancements. We welcomed additional collaborators who expanded the model to several other countries and regions. Switch has been used as the basis of numerous publications as well as reports to state and national agencies, regional development banks and other stakeholders, and has received recognition from the UN. Going forward, we are working to increase the accessibility and usability of Switch to increase our collective contributions and impact even more.

Acknowledgments

I am profoundly grateful to numerous people who helped me complete my graduate studies.

Doctors Jimmy Nelson and Ana Mileva were amazing collaborators. Our long conversations and intellectual explorations enabled me to understand renewable power systems, economics and computational modeling at deeper levels, as well as helping me see how our work fit into a broader context of policy and decision making. Their camaraderie also made the sometimes-bleak landscape of graduate school so much more enjoyable, and I truly value our friendships.

I am very thankful to Matthias Fripp for sharing his time and his initial groundbreaking work that gave us a jump-start in this field of research, as well as for supporting my time in Hawaii where we have been implementing Switch in a new platform that is more accessible and computationally scalable.

I am grateful for my committee chair Daniel Kammen for helping me find a meaningful project that fit my skillsets, for providing support of many forms through graduate school, for standing up for me at times and pushing me to do better at other times, for exposing me to a diversity of experiences and for his unwavering loyalty and support without which I may not have made it through graduate school intact.

I am thankful to my other committee members, professors, fellow graduate students, and advisory committees for giving insightful comments, valuable direction and feedback. I am grateful to all former and current Switch collaborators who helped make this research possible and who are expanding its impact by applying it to new regions and research questions.

I am thankful to my family and friends for helping me through difficult years and maintaining my sanity, especially Kate for her help through the final months of writing.

I am thankful for financial support, hardware donations, software and data from all sources, including the Energy and Resources Group, Class of 1935 Distinguished Professor of Energy chair, the California Energy Commission, the Karsten Family Foundation, the Zaffaroni Family Endowed Fund, Hewlett Packard, IBM, the Center for Information Technology Research in the Interest of Society (CITRIS), the DOE/NREL/ALLIANCE, and all of the developers and companies who contributed to open source software that we rely heavily on.

1 Introduction

1.1 Problem Statement

Global warming is one of the most significant problems facing humanity. Destabilization of weather patterns will wreck havoc on food stability and ecosystem health. Water shortages will be caused by extreme drought as well as decreased glaciers and snow packs that feed rivers in summer months. In the long run, rising sea levels will force large migrations of human populations away from coastal areas, which can increase geopolitical tension and the likelihood of conflicts (Department of Defense, 2014). Global warming is already causing catastrophic consequences including increased storms, floods, droughts and fires, and we are are locked into a certain amount of continued effects. In the years ahead, both mitigation and adaptation will be important. My work focuses on mitigation through emissions reductions, or decarbonization, of the electricity sector.

The electricity sector is the single largest source of global greenhouse emissions (Pachauri, Allen et al. 2014), the majority of which are carbon dioxide released from burning fossil fuels. Decarbonizing electricity is a vital step in economy-wide emission reductions. Transportation and heating are also significant consumers of fossil fuels, and one of the most viable paths to decarbonizing those sectors is shifting their energy demands to electricity. However, that strategy only works if electricity is decarbonized.

Electric power grids are some of the most complex machines humans have built. Electric grids can span half a continent or more, and every generator in a grid must be kept synchronized with every other generator. Energy production and consumption must be balanced at every moment or the grid will shut down to avoid damaging expensive infrastructure. The flows of energy through large AC grids are so complex that no single individual fully understands them (Von Meier, 2006). We rely on computer simulations to approximate system behavior for planning and operations purposes, but our electricity systems are so complex that we cannot model all relevant parameters and contingencies with complete accuracy. Planning and operating electric grids reliably has always been a difficult task, and this task becomes even harder with decarbonization.

Decarbonization poses new challenges to electric power system planning because it requires unprecedented amounts of intermittent renewable generation that introduces significant stochastic elements into grid operations. Technological developments could change this story, but for now the largest technologically accessible and culturally accepted sources of clean electricity are wind and solar. Alternative low emission sources tend to be unproven, controversial, or not available at large scale. Nuclear and Carbon Capture and Sequestration have low emissions, but both are controversial and CCS is somewhat experimental. Hydropower has low direct emissions, but generally creates tremendous environmental problems and displaces large populations when deployed at large scale. Also, most hydropower potential has been developed in industrialized nations. Geothermal has low direct emissions and few environmental or human impacts, but its potential is strongly limited in most areas. Biomass energy has low direct emissions, but potentially high environmental and land use impacts if deployed at scale. The exploitation of biomass can dramatically disrupt the soil carbon cycle and otherwise cause large indirect emissions, depending on how it is deployed. While all of these options and others are on the table, wind and solar are the most proven and accepted low-emission generators that can be deployed on a large scale.

Historically, capacity expansion models could reasonably assume that the vast majority of generation units were baseload or dispatchable which could generally be modeled with deterministic methods. The variability and uncertainty associated with load was fairly small and could be modeled as deterministic reserve requirements. Outages are also random events with low probability and high impact, but these too can be approximated with various deterministic reserve requirements in planning models.

Intermittent renewable generators increase the complexity of the planning process by introducing more uncertainty. The power output of an individual intermittent generator cannot be predicted with precision and has larger deviations than loads. However, renewable power output is not an independent random variable because weather influences the output of other intermittent generators as well as the system demand. For example, clouds can decrease solar panel output while increasing demand for lighting and potentially changing HVAC demand. Consequently, intermittent power is best modeled as a random variable with a complex joint probability distribution that is often approximated from time-synchronized historical records. Approximation methods used for contingency planning (i.e. various types of reserve requirements) can be adapted to deal with intermittent generation, but care needs to be taken in estimating reserve requirements. For example, a simple method that scales output of a single solar installation to approximate the output of a region-wide solar portfolio will significantly overestimate the variability of power output on several timescales (Mills, 2010).

Integrating small amounts of renewable energy is relatively straightforward because the rest of the system can absorb its variability. Integrating large amounts of renewables is more difficult because the existing system was not built to accommodate large amounts of renewable energy. High penetrations of renewables also cause the economics of existing fossil plants to shift as their energy is displaced with renewable power. In general, the complexities of integrating large amounts of intermittent renewable generators requires a new class of planning models that provide high temporal and geographic resolution to endogenously consider integration requirements and invest in new assets that can accommodate larger amounts of renewable energy. Unfortunately, most renewable planning is still performed manually in an ad-hoc manner that does not optimize overall system costs and performance.

Overall, the scale and complexity of a global transition to a cost effective, low-emission, and high-renewable electric power grid requires a large labor force. The scope is larger than what an individual or small research team can effectively accomplish and scale. Global warming mitigation in the electricity sector will proceed most effectively if people adopt collaborative work practices that enable them to readily reuse and extend each other's work. Open collaborative practices can reduce duplication of effort and allow innovations and best practices to spread quickly.

Research Goals

My overall research goals are to contribute to collaborative science by improving a state of the art open source electricity sector planning tool (Switch) and to use this tool to study mitigation pathways. Other more specific goals have arisen from these overarching themes, including:

- Understanding how to practice and promote open collaborative research.
- Identifying least-cost transition plans to drastically lower electricity-sector emissions in the western portion of North America.
- Investigating implications of breakthrough technologies such as low cost solar and Biomass Energy with Carbon Capture and Sequestration.
- Investigating the roles of natural gas in a low emissions grid and the implications of methane emissions in its supply chain.
- Making the Switch model more accessible to more researchers.
- Using significantly more data to evaluate the Switch model and address shortcomings such as capacity shortfalls and emission overruns.

1.2 Energy models

As increasing amounts of renewable generation is integrated into electrical power grids, there is an increasing need for system-level modeling that can account for interaction between components and trade-offs. Besides adding to the complexity of dispatch and adequacy planning, renewable power shifts how the rest of the system is used, generally lowering overall capacity factors of dispatchable fossil plants and increasing the frequency and magnitude of their ramping. This in turn changes the economics of fossil plants whose levelized costs are strongly driven by their capacity factors. Historically, most available capacity has been dispatchable to some degree, which makes planning a portfolio and assigning capacity factors a-priori without dispatch simulation relatively straightforward. With significant amounts of renewables in the system, it is not possible to accurately assign cost-effective capacity factors without performing a dispatch simulation. Traditionally, capacity planning models have not endogenously included dispatch simulations because it was unnecessary and added significant computational burden.

Two leading energy investment planning models used in the United States are the National Energy Modeling System (NEMS) developed by the Energy and Information Administration and the Regional Energy Deployment System (ReEDS) developed at the

National Renewable Energy Laboratory (NREL). NEMS is a general equilibrium energy-economic model that simulates U.S. energy markets with relatively low geographic resolution (15 regions for electricity markets) on a long time horizon. NEMS does not lend itself to renewable integration studies because its electricity module does not capture the temporal relationships between intermittent generation and load. ReEDS is an optimization model of the US electric power grid with relatively high geographic resolution (134 balancing areas) and a long time horizon. ReEDS uses time-synchronized estimates of intermittent generation and load, but has limited temporal resolution with only 34 time slices representing each investment period. ReEDS has two year long investment periods that are solved sequentially without foresight of future constraints such as carbon caps. Several detailed renewable integration models have been developed for small geographic areas or short time horizons, but these models tend not to scale to large geographic areas or planning over long time horizons. ReEDS was designed to support renewable energy planning requirements, however it is not open source or accessible to researchers outside of NREL so is incompatible with open collaborative research.

Given this context, Switch was written to endogenously include sufficient dispatch details to approximate renewable integration requirements and the behavior of the rest of the system. This is an improvement over traditional methods as well as most current renewable integration studies because it simultaneously optimizes all parts of a grid rather than solely focusing on incremental renewable additions while leaving the rest of the grid as a given. Switch also can incorporate long time horizons, which better estimate the value of a durable grid asset that is installed in the near term. Studies that do not consider ratcheting carbon caps could over-invest in technologies that are incompatible with long-term emission goals but have marginally lower emissions than present day generators. For example, over-deployment of fossil-fuel combined heat and power generators would decrease emissions in the short term but result in stranded assets and overall higher grid costs in the long run compared to electrifying those heating loads and using renewable generators to provide electricity. Overall, these capabilities allow Switch to identify more cost-effective solutions than many other approaches.

1.3 Switch Overview

The SWITCH optimization model attempts to capture high levels of geographic and temporal detail in a single investment framework. SWITCH generates a multi-decadal investment plan for the power grid that minimizes the wholesale cost of electricity while meeting load, reliability and policy constraints (Nelson, Johnston et al., 2012). SWITCH and ReEDS are relatively unique among capacity expansion models because they both include a simplified model of day-to-day operations of a large, interconnected power grid. SWITCH was originally developed by Dr. Matthias Fripp to study renewable integration in California (Fripp, 2008). Collaborators and I subsequently expanded the model to the Western Electricity Coordinating Council and enhanced it by including additional technologies, policy constraints and features (Nelson, Johnston et al., 2012; Mileva, Nelson et al., 2013; Wei, Nelson et al., 2013; Sanchez, Nelson et al., 2015). The version of SWITCH used for modeling the Western Electricity Coordinating Council has 50 load areas, about 7,000 intermittent renewable energy sites, and 144 time points per investment period. All load and intermittent generation data is drawn from time-synchronized historical records to capture temporal and geographic relationships.

SWITCH is formulated as a single large linear program with an objective function that minimizes the net present value of the costs associated with meeting electricity demand over its planning horizon. SWITCH includes investment decision variables for transmission, traditional generation and intermittent generation as well as dispatch decision variables representing day-to-day operations. The optimization is subject to a range of constraints including capacity reserves, ancillary services, resource availability, and policies. This type of long-term capacity expansion model can be a valuable tool in assessing the costs and dynamics associated with climate stabilization policies, and potentially informing actual investment decisions.

In several ways SWITCH and ReEDS are comparable, but an important difference is SWITCH is open source while ReEDS is not publically available in any form. Improvements to the SWITCH model consequently can be more accessible to researchers and planners, resulting in a larger impact. SWITCH is also being used to model other power systems including China, Chile, Nicaragua, Hawaii and Japan, so improvements made to the core model can also be applied to other regions.

How Switch can be used:

1. Developing cost-effective emission reduction pathways
2. Evaluating impact of different policies on technical optimums
3. Understanding system dynamics, technology/policy interactions
4. Informing near- and long-term policy
5. Identifying what innovations are needed when to contain costs

Some innovations can take a long time to develop, commercialize, and produce at scale so if we want to deploy them at scale in a few decades, we need to start working on them soon. For example, low- or zero-emission balancing assets such as storage or demand response have low value in the next few decades while weak carbon caps permit cheap natural gas to outcompete them, but become increasingly valuable in 2040 and 2050 when tight carbon caps limit the use of natural gas. This tells us we need to start developing those technologies now so that we can deploy them at scale in a few decades, and that it will be uneconomical to deploy them at scale in the near term while lower cost alternatives remain available.

1.4 Structure of the dissertation

The structure of this dissertation is as follows. Chapter one justifies the need for reducing emissions from the electricity sector and provides context for systems-level planning and collaborative efforts. Chapter two explores the need for open collaborative practices in this arena and describes what adjustments to the status quo could allow us to achieve more benefits from these practices. Chapter three describes results of using the Switch modeling tool to collaboratively develop emission reduction plans for California and the western portion of North America. Chapter four explores the potential of technological breakthroughs in solar, storage and Biomass Energy with Carbon Capture and Sequestration (BECCS). Chapter five examines the roles of natural gas in a low-emission power grid and the impacts of methane leakage upstream in the fuel supply chain. Chapter six describes various improvements to the Switch model that I led and includes reflections on the collaborative process of model development. Chapter seven concludes the dissertation with a discussion of what has been achieved so far and future work. Appendix A provides supporting information for the Natural Gas analysis.

2 Open collaborative practices can accelerate global warming mitigation in the electricity sector

This is adapted from a publication being prepared by Josiah Johnston, Ana Mileva, Diego Ponce de Leon Barido, Matthias Fripp, and Daniel Kammen.

Reducing global emissions from the electricity sector is vital for the long-term health and prosperity of our societies and planet. Rapid action will reduce climate risks, while containing costs and avoiding unintended consequences are also important. Widespread adoption of open and collaborative practices will allow us to pursue these goals more effectively by removing barriers to developing mitigation plans, reducing duplication of effort, and enabling more actors to productively engage in public discourse. Open and collaborative practices have enabled transformative advances in other fields of science and technology but are not yet mainstream in energy planning. Federally sponsored research now has a mandate to provide basic open access for publications and data, which extends to energy-related research. This mandate represents significant progress, but more efforts are needed to fully realize potential benefits of open collaborative practices: improved data warehousing, opening analytic tools, and rewarding community contributions and collaborations.

2.1 Background

Our societies must transform our electricity systems over the coming decades to mitigate dire effects from climate change, transitioning from fossil power to lower-emission sources. Given currently available technology and societal preferences, renewable energy from wind and solar will play a significant role in this transformation. Wind and solar produce electricity on variable and uncertain schedules, which adds significant complexity and data requirements to the already-difficult process of planning and operating power grids. Lack of access to datasets, software and research publications can be a significant barrier to applied research, clean energy planning, training and public engagement that is essential to building consensus in an open society. We propose that widespread adoption of open and collaborative practices can accelerate climate change mitigation efforts by lowering those barriers and permitting more actors to productively engage in developing viable plans for a sustainable future. The process of planning low-emission electric power grids in particular is a data- and computationally- intensive process that can benefit tremendously from open-source and open-science methodologies.

There has been long-standing recognition that making medical and public health research publically available provides large benefits to society while reducing risks of epidemics that could impact us all. A similar case can be made for research on global warming mitigation - collective global action to reduce greenhouse gas emissions will help us all.

The open access movement is increasingly becoming mainstream and starting to shift the status quo, due to a combination of grassroots efforts by scientists and federal mandates stipulating that publications and datasets arising from federal funding be publically accessible. Even private funding agencies such as the Wellcome Trust and the Bill & Melinda Gates Foundation have mandated that researchers they fund make their work open access (Kaiser, 2014; Trust, 2015). While these policies represent a tremendous milestone, additional steps are needed to fully realize the benefits of open collaborative practices.

2.2 Recommendations

First, researchers need to provide software, documentation and a complete list of steps needed to replicate their work. In theory this is a cornerstone of scientific process, but in practice, the majority of published research provides insufficient information for experimental replication (Vasilevsky, Brush et al., 2013). Compiling those materials and providing adequate documentation can require significant work, and researchers may have concerns that releasing full information may cause them to lose a competitive edge in future research. However, in the long run, access those materials will reduce the work required for research by providing better starting points. In regards to the competition concern, there is also the possibility that providing those materials to others can increase citations and overall impact of one's work. Some journals, such as Nature, require authors to supply complete datasets when submitting papers for review and strongly encourage releasing source code, basic documentation and input parameters if the paper is accepted. Nature Methods argues that, "The usefulness of computational methods can be improved by releasing code and designing software that supports reproducible research." (Nature Methods, 2014) The global community would be well served if energy journals encouraged authors to adopt these practices.

Second, policies should shift from "public access" that is read-only to "open access" that encourages the community to replicate, extend and redistribute research products. For research publications, this can enable translations and inclusion in classroom or training material. Free and open access is especially important for data and software so the research community can build upon prior work rather than replicating efforts. This will also enable practitioners such as energy consultants to directly apply research products to relevant problems. Open collaborative practices create many business opportunities for experts to apply complex state-of-the-art methods to real world problems and interpret results. This is a shift from traditional software/data business models that extract value from artificial scarcity of restricting access, and instead creates value from applying expert knowledge and training others.

Third, institutions need to support structured and curated repositories for data and analytical tools that are easy to use, have support staff and invite community engagement. This type of repository is relatively new for renewable energy, so institutions should look at other mature scientific repositories to determine best-practices and avoid common mistakes. In particular, there is a clear need for structured repositories for geographically and temporally resolved renewable energy potential, generator cost and performance characteristics, detailed load profiles, and maps of the existing grid that have sufficient resolution for planning purposes but avoid the level of detail that causes them to be a security concern. The status quo for publically accessible data is for it to be scattered across disparate websites with distinct interfaces and formats, often with scant documentation or quality control. Compiling and curating this data is a common and incredibly time-consuming task for most researchers, and there are currently few incentives or mechanisms for them to share their work products with a broader community. Managing a comprehensive and easy-to-use repository is a significant data science problem that is beyond the capabilities or job descriptions of individual researchers. Under these circumstances, institutional support for repositories can provide tremendous benefits, especially if researchers' contributions are valued during job review and promotions. However, if an institution seeks to completely develop and maintain a repository without community input or review, the repository is unlikely to be scalable or serve as a platform for community discussion and consensus building. Emerging energy-based repositories tend to pull unstructured data into a central location, which is an important first step but not ideal for the long term because similar data for different locations can be formatted in distinct idiosyncratic ways that reduces software reuse and slows the development of large-scale analysis.

Fourth, researchers and repositories should use best practices from data science regarding interoperability, record keeping and replicability. Interoperability entails using standard formats for data so that researchers and policy analysts can focus more on asking relevant questions and less on reformatting data for a particular software tool. Interoperability also means that different software tools or models that accomplish distinct goals can be connected more readily to ask larger questions or conduct economy-wide mitigation planning. Record keeping and replication mean that every analytic step from inputs to results is fully recorded and archived. Part of this is enabled by software design that supports scripting and/or history tracking, and part is enabled by training researchers in best practices of scientific computing.

2.3 Institutional context

Fortunately, there is a growing recognition that open and collaborative practices are valuable and desirable. Beginning in 2005, the National Institutes of Health (NIH) spearheaded an public access policy mandating that all publications and data arising from research it sponsors be made publically available free of charge (National Institutes of Health, 2008). The NIH maintains a central archive of publications (PubMed), and numerous data archives that invite community contributions while providing staffing for curation, quality assurance, and server administration (GenBank, ChemBank, etc). A White House Directive in 2013 gave a similar public access mandate for all major federally funded scientific research (Holdren, 2013). The Department of Energy (DOE) chose to implement a weakened form of the NIH model (Department of Energy, 2014), where they provide links to publishers' websites rather than maintaining a central archive, an approach that the NIH believes offers fewer benefits (National Institutes of Health, 2014). Neither agency has mandates for "Open Access" that would allow publications to be redistributed (e.g. in printed form for training or classroom materials) or used for derivative work such as translations, which can significantly hinder global impact of the research products. The DOE currently offers scant guidelines or coordination in regards to data, merely requiring that researchers somehow make their digital data publically available, but are actively taking steps to address this gap.

2.4 Status Quo

Identifying cost-effective and politically viable development pathways to sustainable energy systems requires basic research, applied research, planning efforts, and significant public discourse. At each stage, lack of access to data, computational tools and research findings can be a significant barrier to progress. Geographically resolved descriptions of existing infrastructure are typically proprietary and/or kept secret as part of an effort of "security by obscurity". High resolution datasets of renewable energy availability and electricity demand are often only available through expensive proprietary sources that often prohibit researchers from sharing their datasets with others. Modeling platforms and optimization tools are generally both expensive and proprietary. The majority of research publications are still behind paywalls and are often inaccessible to practitioners, government agencies, nonprofits, and even many universities that cannot afford subscription fees. Collectively, these barriers significantly impede work of professionals and training of an expert labor force for the future. This is very problematic given an urgent need for collective action on climate change mitigation and energy security; any barriers to progress in these areas hurt us all.

Individual institutions have constructed repositories of renewable energy potential from their own studies, such as the National Renewable Energy Lab's datasets from renewable integration studies (Corbus, King et al., 2010; Lew, Piwko et al., 2010), or the Global Energy Atlas (International Renewable Energy Agency, 2015). These data repositories are still relatively weak at integrating community contributions while being easy-to-use, but IRENA appears to be making efforts to improve. The DOE's Geothermal data repository focuses on collecting community contributions, but it currently is an unstructured collection that is difficult to browse or navigate.

2.5 Discussion

Open collaborative practices can provide many benefits to society, researchers, funding agencies and businesses. They can accelerate the speed and quality of innovation, research & implementation by enabling agile project management and reducing duplicated effort. Under agile methods, a new project often starts with a similar existing and validated work product then applies incremental changes to meet new goals. During this process people often work in pairs, which results in fewer errors, higher quality work products and increased knowledge transfer between workers. Agile techniques have proven extremely effective in manufacturing, software development and research. If researchers are more intentional about making their work easily replicated and starting new projects from prior validated work, they can contribute to a more comprehensive, coherent and validated body of work.

Open and collaborative practices can enable a smoother transition to a clean electric grid by removing information barriers, streamlining research efforts and providing materials for students and educators. This is particularly important for less wealthy countries, NGOs, small companies, and educational institutions. Streamlined research and training should create cost savings in the resulting power system from more innovations as well as engineering and economic insights. More importantly, open practices can increase the quality of public discourse by enabling stakeholders to be well informed. This could reduce public opposition to well-intentioned projects by reducing information asymmetry, enabling stakeholders to construct alternative candidate portfolios and understand the costs or environmental tradeoffs of their preferences.

The benefits of open practices are broadly recognized, resulting in large amounts of open data, mostly from government sources. Most new cutting edge research involves large complex projects that are too large for any single person or small group to tackle individually. Global warming mitigation requires larger coordinated efforts, and strategic practices such as open access and open source can enable greater coordination. We argue that society would benefit from accelerating open collaborative practices, and that these practices are particularly valuable for the computationally intensive task of planning renewable power systems and designing candidate investment portfolios.

2.6 Switch and Open Collaborative Practices

The Switch model is a good example of how open collaborative research can accelerate research and enable greater progress than would otherwise be possible, especially in an academic environment. The ideas behind Switch and the model itself were developed over several years by a single PhD student, Matthias Fripp, who scrambled to assemble a useful model and datasets for California. Once completed, he shared it with our larger team of students who had the resources to assemble datasets for the entire Western Electrical Coordinating Council (WECC), update costs and descriptions of generation technologies, explore relevant policy perspectives and expand the model's functionality to add realism. The expansion of the model into WECC would probably not have been possible for Matthias to complete by himself because the data and policy landscape would been changing faster than he could assemble datasets. A larger team is required to maintain an adequate research pace to assemble and analyze large-scale datasets in a dynamic and changing landscape. If our research team had attempted this type of analysis for WECC without basing it on prior work, it is unlikely we would have made adequate research progress with proof-of-concept goals to maintain funding that allowed us to complete the analysis.

Once we published a paper on Switch-WECC and developed relationships in the larger California energy research community, it was easier for us to secure additional funding to continue expanding the scope of the analysis and depth of the model to pursue research questions that emerged from our first rounds of research. As our expertise and reputation grew, it became easier to attract other talented researchers who wished to apply Switch to other countries. They also experienced similar bootstrapping dynamics where building off of our previous work enabled them to establish proof of concepts rapidly enough to secure funding to continue their research in a rigorous manner.

Throughout this process we attempted to follow best practices of open collaborative practices but were not always able to meet gold standards. For example, we preferred to publish with open access options, but were not always able to afford the additional fees. As a work-around, we posted those publications on the lab's website as well as other public repositories such as Research Gate in order to make our research findings accessible to others. In regards to source code and datasets, we also took a second-tier approach of providing complete examples on request to other researchers and attempting to provide technical support on a best-effort basis. It would have been more ideal to post them directly to public archives but at the time of our earlier publications, we were not aware of any available free archives that could handle our large volumes of data. That situation has changed, and I plan to post complete run directories of input data, source code and results to accompany an upcoming paper on the impacts of methane emissions in a low-emission power grid. Although our code and data from prior research was not posted publically, we have shared it when requested to other researchers, which resulted in two separate collaborations with research centers in Canada and Chile. These collaborations look promising and should result in publications within the next six to twelve months.

Moving forward, we are taking large strides to make Switch more open and accessible. We are in the process of writing a new version of Switch that uses a completely open source software stack, and are storing this code and example datasets in a public GitHub repository. This open version has already attracted interest from two additional outside organizations – an energy consulting firm and google – who are actively contributing code, documentation, and testing services to the project. I hope that this open version can expand into a platform for research, policy analysis, and consulting services. With luck, we will able to leverage successes to date to fund our efforts to make this more accessible and usable. Ideally, we could find an institutional home to support these efforts and partner with emerging data portals to make the process of assembling datasets for Switch much easier and faster. Publications and press releases describing this effort should be forthcoming this fall.

3 Planning Mitigation Pathways for California and Western North America

Between 2008 and 2013, I worked with a team of researchers to expand the geographic scope and modeling capabilities of the Switch model and applied it to develop climate change mitigation plans for California and Western North America. This process was an important step in establishing the legitimacy of Switch as a robust and general planning platform, as well as ensuring that it can produce relevant and useful results. We expanded the geographic scope from California to the entire Western Electricity Coordinating Council to avoid a common modeling problem of reshuffling high-emission plants to outside the boundaries of the model and to enable integration of high quality renewable resources from the desert southwest and the great plains. We simultaneously expanded the modeling capabilities of Switch to more accurately reflect existing policies and technical requirements of electricity grids based on requests from technical and policy advisory committees. This chapter summarizes results from that body of research. It is largely based on our initial publication High-resolution modeling of the western North American power system demonstrates low-cost and low-carbon futures and also includes summaries from four follow-up studies: California's Carbon Challenge Phase 1, Wei et al, 2013, California's Carbon Challenge Phase 2 Vol 1 and Vol 2.

> Decarbonizing electricity production is central to reducing greenhouse gas emissions. Exploiting intermittent renewable energy resources demands power system planning models with high temporal and spatial resolution. We use a mixed-integer linear programming model – SWITCH – to analyze least-cost generation, storage, and transmission capacity expansion for western North America under various policy and cost scenarios. Current renewable portfolio standards are shown to be insufficient to meet emission reduction targets by 2030 without new policy. With stronger carbon policy consistent with a 450 ppm climate stabilization scenario, power sector emissions can be reduced to 54% of 1990 levels by 2030 using different portfolios of existing generation technologies. Under a range of resource cost scenarios, most coal power plants would be replaced by solar, wind, gas, and/or nuclear generation, with intermittent renewable sources providing at least 17% and as much as 29% of total power by 2030. The carbon price to induce these deep carbon emission reductions is high, but, assuming carbon price revenues are reinvested in the power sector, the cost of power is found to increase by at most 20% relative to business-as-usual projections.

HIGHLIGHTS

1. Intermittent generation necessitates high-resolution electric power system models.
2. We apply the SWITCH planning model to the western North American grid.
3. We explore carbon policy and resource cost scenarios through 2030.

4. Coal generation is replaced with solar, wind, gas, and/or nuclear generation.
5. A 450 ppm climate stabilization target can be met at a 20% or lower cost increase.

3.1 Introduction

Decarbonization of the electric power sector is critical to achieving greenhouse gas reductions that are needed for a sustainable future. In the United States, for example, the electricity sector accounts for 41% of U.S. carbon emissions (U.S. Energy Information Administration, 2008). A number of low-carbon power generation technologies are available today, but many of them are less flexible than conventional generators. Nuclear and geothermal must be run in baseload mode (steady round-the-clock), while wind and photovoltaics have intermittent, site-specific output. Consequently, it is unclear how these resources should be combined in future power systems. The literature on the cost-reduction potential of individual renewable technologies is extensive, but less research has explored cost and emission reductions achieved by leveraging synergies among a wide range of technologies. Such analyses are needed to aid climate policymaking and to preserve power system reliability while achieving emission reductions at the lowest possible cost.

Existing electric power system models primarily address either day-to-day operation or long-term capacity planning, but not both. Multiple studies have been conducted examining the impact of higher levels of intermittent generation on grid operations (e.g. EnerNex Corp, 2006, GE Energy, 2010, and EnerNex Corp, 2010). These studies evaluate the daily grid operations and costs of specific, predefined deployment levels of renewable energy, but provide little information on how the grid should be developed to achieve policy objectives at the lowest cost. Economic dispatch models (Wood and Wollenberg, 1996) are used in these studies to simulate the operation and production costs of a predefined fleet of generators, transmission lines, and storage systems, but cannot plan optimal capacity additions. In contrast, specialized capacity-expansion models (Kagiannas et al., 2004, DeCarolis and Keith, 2006, U.S. Energy Information Administration, 2009, National Renewable Energy Laboratory, 2010a, Chen et al., 2010) are used to inform long-term planning of generation, storage, and transmission projects, but these models have limited operational resolution. Many models use statistical methods to represent intermittent generators, but are unable to evaluate the dynamic interplay between wind power, solar power, and load. Others are limited in their geographic scope, geographic resolution, or the range of technological options they consider. As long-term grid planning increasingly looks to intermittent generation sources such as solar and wind, the need increases for large-scale, high-resolution modeling that merges the capabilities of capacity expansion and economic dispatch models.

3.2 SWITCH model

Model Introduction

The SWITCH model – a loose acronym for Solar, Wind, Hydro and Conventional generation and Transmission Investment – uses an unprecedented combination of spatial and temporal detail to design realistic power systems and plan capacity expansion to meet policy goals and carbon emission reduction targets at minimal cost (Fripp, 2008; Fripp, 2012). SWITCH is a planning tool for the electric power system (Fig. 3.1, 3.2) that optimizes capacity expansion of renewable and conventional generation technologies, storage technologies, and the transmission system, while explicitly accounting for the hourly variability of intermittent renewables and electricity loads. SWITCH improves on other capacity expansion models by incorporating elements of the day-to-day operation and dispatch of a large, interconnected electric power grid. For this paper, we use SWITCH to investigate decarbonization options for the synchronous region of the Western Electricity Coordinating Council (WECC). WECC includes 11 western U.S. States, Northern Baja Mexico, and the Canadian provinces of British Columbia and Alberta. WECC provides an ideal case to examine system dynamics in a complex, interconnected region with significant greenhouse gas emissions and many low-carbon generation resources.

SWITCH is a mixed-integer linear program whose objective function (Fig. 3.2) is to minimize the societal cost of meeting projected electricity demand with generation, storage, and transmission between present day and 2030. The optimization is subject to reliability, operational, and resource-availability constraints, as well as both existing and possible future climate policies. SWITCH was originally developed to study the cost of achieving high renewable energy targets in California (Fripp, 2008; Fripp, 2012), using existing facilities along with new wind, solar, and natural gas plants. For this study, we have extended SWITCH to include more generation and storage technologies, incorporated a state-based renewable portfolio standard (RPS) requirement, and implemented a post-optimization reliability assessment. The updated model is applied to the entire WECC power system. A description of the version of SWITCH used for this paper is provided below; the complete model formulation is available in the online supplemental information.

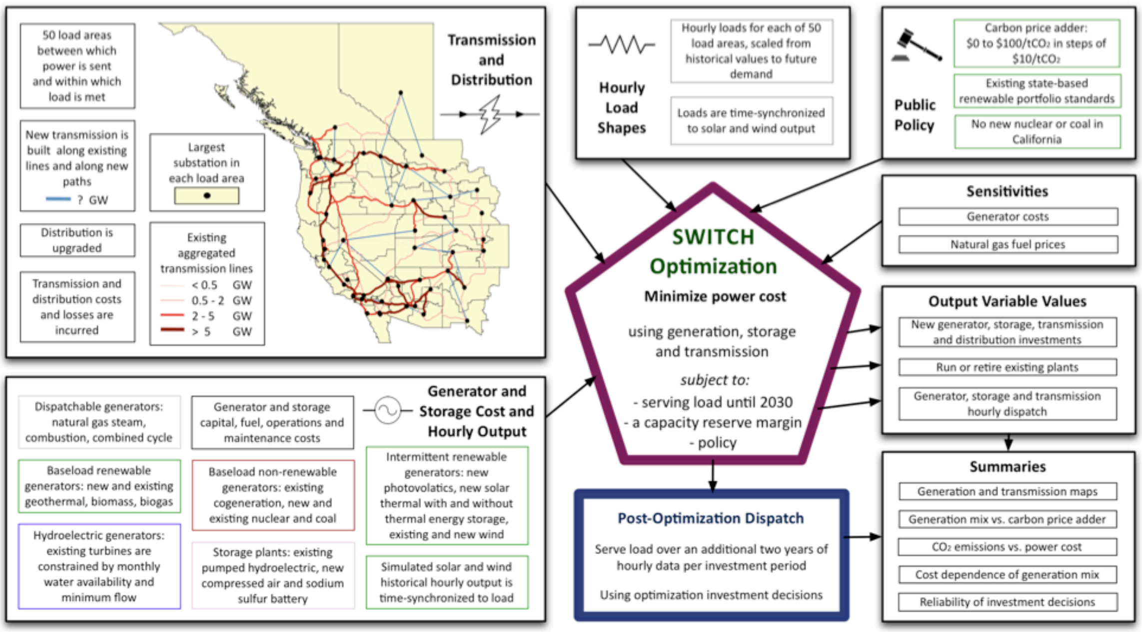


Figure 3.1 Optimization and data framework of the western North American SWITCH model.

Objective function: minimize the total cost of meeting load			
Generation and Storage	Capital	$\sum_{g,i} G_{g,i} \cdot c_{g,i}$	The capital cost incurred for installing a generator at plant *g* in investment period *i* is calculated as the generator size in MW $G_{g,i}$ multiplied by the cost of that type of generator in $2007 / MW $c_{g,i}$.
	Fixed O&M	$+(ep_g + \sum_{g,i} G_{g,i}) \cdot x_{g,i}$	The fixed operation and maintenance costs paid for plant *g* in investment period *i* are calculated as the total generation capacity of the plant in MW (the pre-existing capacity ep_g at plant *g* plus the total capacity $G_{g,i}$ installed through investment period *i*) multiplied by the recurring fixed costs associated with that type of generator in $2007 / MW $x_{g,i}$.
	Variable	$+\sum_{g,t} O_{g,t} \cdot \left(m_{g,t} + f_{g,t} + c_{g,t}\right) \cdot hs_t$	The variable costs paid for plant *g* operating in study hour *t* are calculated as the power output in MWh $O_{g,t}$ multiplied by the sum of the variable costs associated with that type of generator in $2007 / MWh. The variable costs include per MWh maintenance costs $m_{g,t}$, fuel costs $f_{g,t}$, and carbon costs $c_{g,t}$, and are weighted by the number of hours each study hour represents, hs_t.
Transmission		$+\sum_{a,a',i} T_{a,a',i} \cdot l_{a,a'} \cdot t_{a,a',i}$	The cost of building or upgrading transmission lines between two load areas *a* and *a'* in investment period *i* is calculated as the product of the rated transfer capacity of the new lines in MW $T_{a,a',i}$, the length of the new line $l_{a,a'}$, and the regionally adjusted per-km cost of building new transmission in $2007 / MW · km, $t_{a,a',i}$. Transmission can only be built between load areas that are adjacent to each other or that are already connected.

Distribution		$+\sum_{a,i} d_{a,i}$	The cost of upgrading local transmission and distribution within a load area *a* in investment period *i* is calculated as the cost of building and maintaining the upgrade in \$2007 / MW $d_{a,i}$.
Sunk		$+ s$	Sunk costs include ongoing capital payments incurred during the study period for existing plants, existing transmission networks, and existing distribution networks. The sunk costs do not affect the optimization decision variables, but are taken into account when calculating the cost of power at the end of the optimization.

Figure 3.2 Optimization objective function. Further information on the objective function and a full description of optimization constraints and state variables not present in the objective function can be found in the Online Supplemental Information.

Geographic Resolution: Load Areas and Transmission

For the purpose of identifying where power is generated and where it is used, we divide the synchronous WECC region into fifty "load areas." These represent areas of the grid within which there is significant existing local transmission and distribution, but between which there may be limited long-range, high-voltage existing transmission. Consequently, load areas are regions between which transmission investment may be beneficial. Power flow between WECC and the Eastern and Texas interconnects is not considered, as less than 2 GW power transfer capacity currently exists between these regions (Ventyx Corp, 2009), relative to WECC peak load of more than 150 GW.

A total of 124 existing and new transmission corridors between pairs of load areas are included in each optimization. Existing transmission capacity is determined from Federal Energy Regulatory Commission (FERC) data on the thermal limits of individual power lines (Federal Energy Regulatory Commission, 2009). New high-voltage transfer capability can be built along existing transmission corridors at a cost of \$1,000/MW·km. If no transmission exists between two adjacent load areas, new capacity can be installed at a cost of \$1,500/MW·km.

SWITCH does not currently model the electrical properties of the transmission network in detail and, as such, is not a power flow model based on Kirchhoff's laws. Optimal power flow models identify the least expensive dispatch plan for existing generators to meet a pre-specified set of loads, while respecting the physical constraints on the flow of power on every line in the network (Bergen and Vijay, 2000). They become non-linear when investment choices or AC properties are included, making them computationally infeasible for optimizing the evolution of the power system, especially over a large area and many hours. Instead, SWITCH treats the electrical transmission system as a generic transportation network with maximum transfer capabilities equal to the sum of the thermal limits of individual transmission lines between each pair of load areas. SWITCH models the capabilities of the transmission network, and the cost of upgrading those capabilities, rather than simulating the physical behavior of the transmission network directly.

Temporal Resolution: Investment Periods and Dispatch Hours
To simulate power system dynamics over the course of the next twenty years, SWITCH employs four levels of temporal resolution: investment periods, months, days, and study hours. For our analysis, there are four four-year-long investment periods: 2014-2017, 2018-2021, 2022-2025, and 2026-2029, each of which contains historical data from 12 months, two days per month, and six study hours per day. This results in (4 investment periods) x (12 months/investment period) x (2 days/month) x (6 hours/day) = 576 sampled hours over which the system is dispatched. The peak and median days from each historical month are sampled to represent a large range of possible load and weather conditions over the course of each investment period. Each sampled day is assigned a weight: peak load days are given a weight of one day per month while median days are given a weight of the number of days in a given month minus one. This weighting scheme ensures that the total number of days simulated in each investment period is equal to the number of days between the start and end of that investment period, emphasizes the economics of dispatching the system under typical load conditions, and forces the system to plan for capacity availability at times of high grid stress (Fripp, 2008).

Infrastructure Investment and Dispatch
The SWITCH model includes two main sets of decision variables: capacity investment variables and dispatch variables. At the beginning of each of the model's investment periods, capacity investment decision variables determine the amount of new capacity to install of each generator or storage type, the amount of transmission capacity to add along each transmission corridor, and whether to operate or retire each existing non-hydroelectric power plant. The power output of baseload (coal, nuclear, geothermal, biomass, biogas, cogeneration) and intermittent (solar and wind) generation is specified through capacity investment decision variables. For baseload generators, the power produced in each hour is equal to the generator capacity de-rated for forced and scheduled outages. For intermittent generators, the power produced in each hour is equal to the generator capacity multiplied by an exogenously calculated capacity factor for that hour.

In each study hour, dispatch variables control the amount of power to generate from each dispatchable (hydroelectric or natural gas) generator, the amount of power to store and release at each storage facility (pumped hydroelectric, compressed air energy storage, or sodium-sulfur battery), and the amount of power to transfer along each transmission corridor. Storage projects must meet an energy balance constraint over the course of each study day. Similarly, the dispatch of hydroelectric projects over the course of each study day is constrained to equal average historical monthly generation. Hydro projects must also meet a minimum flow requirement in each study hour. All dispatch decisions are subject to capacity constraints set by investment decision variables. However, the hourly dispatch of generation, transmission, and storage within each investment period is optimized concurrently with investment decisions: in the SWITCH optimization framework, dispatch and investment decisions are made simultaneously rather than iteratively.

Operational and Policy Constraints

The model includes three main sets of constraints: those that ensure that projected demand is met, those that maintain the reserve margin, and those that enforce RPS.

The first set of constraints requires that the available power system infrastructure is dispatched to meet load in every hour in every load area while providing the least expensive power based on expected generation, storage, and transmission availability. The nameplate capacity of grid assets is de-rated by their forced outage rates to represent the amount of power generation capacity that is available on average in each hour. Baseload generator output is further de-rated by the scheduled outage rate of each generator.

To further address system risk, a second set of constraints requires that the power system maintain a planning reserve margin at all times, i.e. that it has sufficient capacity available to provide at least 15 percent extra power above load in every load area in every hour if all generators, storage projects and transmission lines are working properly. In calculating the reserve margin, the outputs of these grid assets are therefore not de-rated by forced outage rates. SWITCH determines the reserve margin schedule concurrently with the load-serving dispatch schedule.

The set of RPS constraints ensures that a minimum fraction of load is met with renewable energy sources in each investment period in each load area. This fraction is consistent with current state RPS targets. Procurement of renewable energy credits from areas outside WECC is not considered.

Dispatch Verification

While each optimization considers a large number of study hours, the proposed power system must also successfully meet load on many more possible states of load and renewable resource availability than are input into the core optimization. Consequently, the grid’s ability to meet load in hours other than the 576 study hours used in the optimization is assessed by fixing all investment decision variables, uploading new hourly datasets, and optimizing dispatch for lowest cost. In total, investment decisions made in each of the four investment periods are dispatched over 16,800 historic hours (almost two years) from 2004 and 2005, in batches of weeks.

Similar to the investment optimization, dispatch verification does not include forecast error, unit commitment, generator ramping constraints, security constraints, or load flow transmission constraints. Flow on transmission corridors is constrained to not exceed their thermal limits, but power flow equations are not explicitly solved. Further work will investigate power system behavior under strict operational constraints.

Costs

The present day capital cost of building each type of power plant or storage project is reduced via an exponential decay function using a capital cost declination rate (Fig. 3.3). The capital cost of each project is locked in at the first year of construction. Construction costs for power plants are tallied yearly, discounted to present value at the online year of the project, and then amortized over the operational lifetime of the project. Only those payments that occur during the study period are included in the objective function. The cost to connect new power plants to the grid is incurred in the year before operation begins. Operation and maintenance costs are incurred throughout each project's operational lifetime.

For optimization purposes, all costs during the study are discounted to a present day value using a real discount rate of 7%, so that costs incurred later in the study have less impact than those incurred earlier. The discount rate is based on the base case from the White House Office of Management and Budget's Circular A-94, "Guidelines and Discount Rates for Benefit-Cost Analysis of Federal Programs" (White House Office of Management and Budget, 2010). All costs are specified in real terms, indexed to the reference year 2007.

Coal and natural gas fuel prices are as specified in the reference case of the United States Energy Information Agency's 2009 Annual Energy Outlook (U.S. Energy Information Administration, 2009), with coal and natural gas reaching average prices of \$1.52/MMBtu and \$8.13/MMBtu in \$2007 respectively by 2030. Uranium price projections are taken from the California Energy Commission's 2007 Cost of Generation Model (Klein and Rednam, 2007) and reach a price of \$2.20/MMBtu by 2030. Solid biomass costs are included through a piecewise linear supply curve. Yearly fuel price projections are averaged over each investment period. Fuel price elasticity is not currently included.

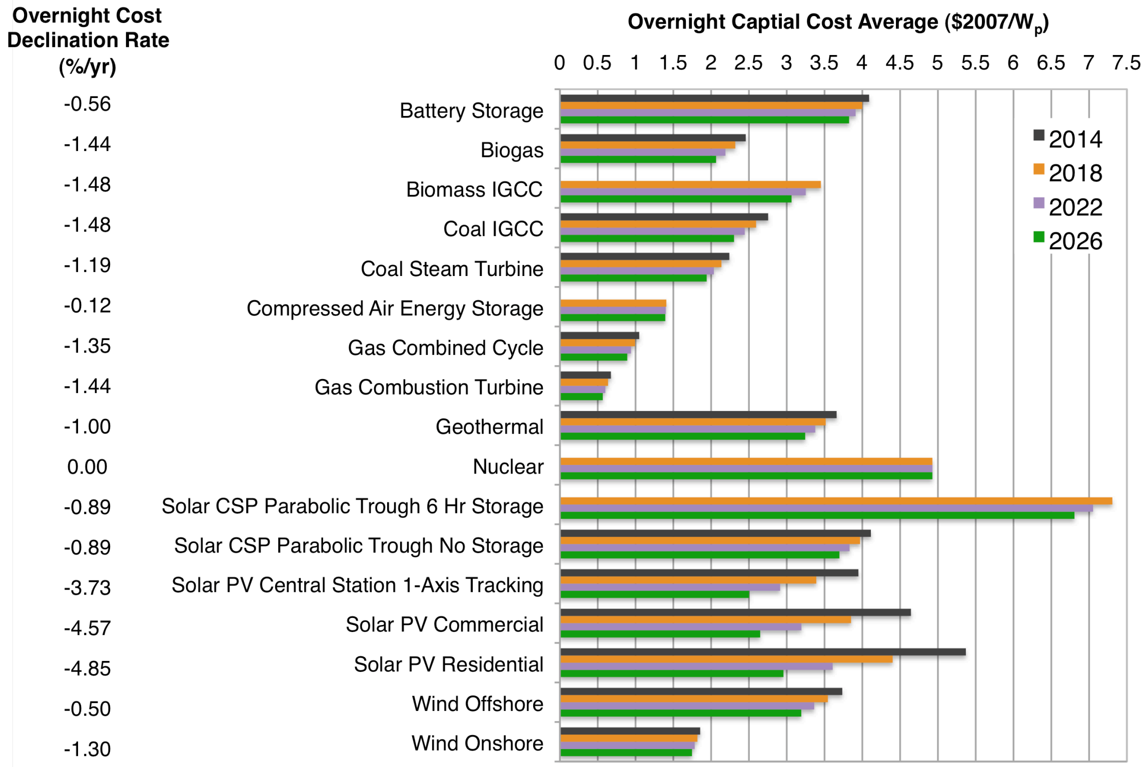


Figure 3.3 Annual overnight cost declination rates and overnight capital costs by investment period in the Base Cost scenario for each generator and storage technology. Costs for technologies not available for installation in 2014 are not shown. CSP denotes concentrating solar power (solar thermal). Many of these values are varied in generator cost sensitivity scenarios described in Section 3.3. Overnight capital costs do not include regional capital cost multipliers, interest during construction, grid connection costs, local grid upgrade costs, and operations and maintenance costs, though these costs are included in each optimization. See the Online Supplemental Information for more information.

Load and Resource Data

Electricity demand and intermittent renewable output are both dependent on weather conditions. We use simulated historical hourly generation profiles from 2004-05 for a portfolio of 3,362 wind, 3,375 solar photovoltaic (PV), and 2,380 solar thermal parabolic trough systems (also known as concentrating solar power or CSP) sites as well as hourly load profiles that are time-synchronized to the renewable output data. Hourly load data is scaled to projected future demand, while resource availability is used directly from historical data. Using time-synchronized hourly load and generation profiles allows SWITCH to capture the temporal relationship between load and renewable power output levels.

Hourly loads are derived from the Federal Energy Regulatory Commission's (FERC) Annual Electric Balancing Authority Area and Planning Area Report (Federal Energy Regulatory Commission, 2005) and apportioned to load areas.

Hourly wind turbine output is obtained from the 3TIER wind power output dataset produced for the Western Wind and Solar Integration Study (WWSIS) (3TIER, 2010). Hourly solar generation output is derived by merging 10km-resolution gridded satellite insolation data from the State University of New York (SUNY) (Perez, Ineichen et al., 2002; National Renewable Energy Laboratory, 2010a) and ~38km-resolution weather data from the National Center for Environmental Prediction's (NCEP) Climate Forecast System Reanalysis (CFSR) (National Climatic Data Center, 2010; Saha, Moorthi et al., 2010). The resultant weather files are used as inputs to the National Renewable Energy Laboratory's Solar Advisor Model (National Renewable Energy Laboratory, 2010b) to calculate the simulated historical output of various types of solar projects.

A broad range of generation options and their projected costs are input into each optimization (Fig. 3.1, 3.3). The model can select from nearly 10,000 possible wind, solar, geothermal, biomass, biogas, nuclear, coal, and natural gas power plants to install and operate in each investment period.

Large existing thermal generators in WECC are included (Ventyx Corp, 2009), totaling 578 power plants, each of which is given a binary decision variable to operate or not during each investment period. Once retired, an existing generator cannot be re-started. The hourly output of 232 existing wind farms is also included. Existing hydroelectric generators are aggregated to the load area level, operated subject to streamflow constraints, and cannot be retired. Existing pumped hydroelectric storage plants are included, as well as the option to install new compressed air energy storage (CAES) and sodium-sulfur (NaS) battery storage projects.

Carbon capture and sequestration (CCS) is a low-carbon technology that may compete with nuclear and/or renewable power. This technology is still at a prototype phase, and its feasibility and future costs are uncertain (McKinsey & Company, 2008). Future work will include CCS as well as other early-phase technologies.

Implementation

SWITCH uses a layered architecture consisting of data stores, middleware, a high-level modeling language, and a Mixed Integer Program (MIP) solver. Non-spatial data are stored in MySQL while spatial data are stored in PostgreSQL/PostGIS. The SWITCH model is written in AMPL, a high level mathematical programming language. AMPL compiles a MIP for a particular set of inputs and policy options, which is passed to CPLEX for optimization. For this study, a typical cost optimization problem has a reduced MIP with approximately 800,000 constraints, 800,000 linear decision variables, and 2,000 binary variables. The middleware that reformats data and manages execution is a collection of BASH shell scripts. The optimizations run on a cluster of IBM Dataplex server nodes, each containing two 2.7 GHz quad-core processors and 24GB of RAM.

Future Model Development

SWITCH captures many important dynamics of the electric power sector at high resolution but the inherent complexity of the electric power system necessitates even greater detail in many areas. Work is underway to integrate sub-hourly ancillary services such as regulation, spinning, and non-spinning reserves, which will provide additional assurance of grid reliability. The inclusion of additional hours during the investment optimization is also a near-term priority in order to develop more finely tuned investment plans. Further extensions will examine the large-scale deployment of electric vehicles, load response, and robustness of energy scenarios to climate impacts on the electricity system.

3.3 Scenario Descriptions

We use SWITCH to investigate the carbon emissions from and cost of power in the WECC power system under multiple realistic generator cost and fuel price scenarios (Table 3.1), and under varying carbon policy. In all scenarios investigated here, consistent with current policy, existing state RPS targets are met, and new nuclear and coal generation are prohibited from being built in California.

Scenario Name	**Scenario Description**
Base Cost	Generator overnight capital costs and capital cost declination rates are as shown in Figure 3. Natural gas prices are as described in Section 2.7.
Low Nuclear Cost	The overnight capital cost of new nuclear power plants is lowered to $4/W from the base $5/W.
Low Gas Price High Gas Price	The inter-annual percentage change in natural gas fuel prices is calculated from the Base Cost scenario. These values are increased by 1% for the High Gas Price scenario and lowered by 1% for the Low Gas Price scenario, and then used to recalculate natural gas fuel prices.
High PV Cost	PV costs are higher than in the Base Cost scenario in all investment periods. This is achieved by reducing the magnitude of the base PV capital cost declination rate (see Fig. 3) by 1.5% percent per year.
Low CSP Cost/ High PV Cost	PV costs are higher and CSP costs are lower than in the Base Cost scenario in all investment periods. This is achieved by lowering the base PV capital cost declination rate (see Fig. 3) by 1.5% per year and increasing the base CSP capital cost declination rate by 2.5% per year.

Table 3.1 Generator cost and fuel price scenarios investigated in this study. For scenarios other than the Base Cost scenario, the 'Scenario Description' column describes the only changes made relative to the Base Cost scenario.

The future costs of generation technologies are highly uncertain. For example, estimates of the capital cost of nuclear power range widely (Harding, 2007; Cooper, 2009). It is also unclear how much public opposition new nuclear plants would face, especially in light of the recent Fukushima Daiichi accident. Reflecting these issues, we model two nuclear capital cost scenarios. The Base Cost scenario assumes a capital cost of $5/W for nuclear plants in order to investigate low-carbon power systems that can be achieved without low-cost nuclear power. The Low Nuclear Cost scenario assumes that nuclear power is available at a capital cost of $4/W in order to explore optimal power system deployment with low-cost nuclear power. In both nuclear cost scenarios, the overnight capital cost of nuclear power is assumed to stay constant through 2030.

Similarly, the rate of technological progress in the solar industry is uncertain, especially in the 2030 timeframe (Tidball, 2010). We model three solar capital cost scenarios. In the Base Cost scenario, the capital cost of PV systems decreases as shown in Figure 3. In the High PV Cost scenario, PV capital costs decline more slowly, reflecting the possibility that the PV industry may not meet future cost targets. Relative to cost assumptions in the Base Cost scenario, overnight capital costs for central station PV in the High PV Cost scenario are 28% higher in the 2026 investment period. In the Low CSP Cost/High PV Cost scenario, CSP costs outperform PV costs: CSP capital costs decline more quickly than in the Base Cost scenario and PV costs are kept as in the High PV Cost scenario. CSP overnight capital costs are 34% lower than in the Base Cost scenario in the 2026 investment period.

Natural gas is an important fuel due to its relatively low carbon intensity as well as its dispatchability and hence ability to compensate for variable renewable output. However, the delivered price of natural gas has historically been difficult to predict. We explore scenarios with a higher and a lower price trajectory for natural gas relative to the Base Cost scenario – the High Gas Price scenario and Low Gas Price scenario respectively – to determine the effect of long-term uncertainty in natural gas prices on the cost of power and the optimal power mix. Natural gas prices reach a WECC-wide average of $6.74/MMBtu in the Low Gas Price scenario and $9.76/MMBtu in the High Gas Price scenario in $2007 by 2030.

Within each cost scenario, we vary an exogenous “carbon price adder” in order to force SWITCH to redesign the power system to achieve a range of CO2 emissions. For each cost scenario, we vary the carbon price adder from $0/tCO2 to $100/tCO2. This adder is held constant through all investment periods for each carbon price adder. The carbon price adder could correspond to a carbon tax or the cost of permits under a cap and trade policy. The revenue from this carbon adder is assumed to be re-invested in the electricity sector and re-distributed to electricity consumers, and as such it does not directly affect the average cost of power (transaction costs are assumed to be negligible). Rather, it does so indirectly, by changing the relative costs of power generating technologies. As the carbon adder is increased, generation from previously inexpensive but carbon-intensive power plants becomes less economically attractive relative to other generation options.

At the end of the optimization, we calculate carbon emissions from the resultant power system for each carbon price adder. In order to stabilize the climate at or below an atmospheric concentration of 450 ppm CO2, the International Energy Agency finds that annual power sector emissions should drop to 54% of 1990 levels by 2030 for Organization for Economic Co-operation and Development (OECD) countries, with further declines thereafter (International Energy Agency, 2008). Below, we discuss power systems that are consistent with this 450 ppm CO2 climate stabilization target, assuming a proportional contribution of the WECC power system, which is part of the OECD, to global emission targets.

3.4 Results

Base Cost Scenario

In the Base Cost scenario, if no carbon policy is implemented (a carbon price adder of \$0/tCO2), the least-cost system would obtain 47% of its power from coal in 2026–29, as shown at the far left side of Figure 4B. This system is similar to present day power systems, and, owing to load growth, emits 194% of the 1990 baseline CO2 level by 2030 (Fig. 3.4A). In the Base Cost scenario, as the carbon adder is increased above \$0/tCO2, a combination of solar, wind, biomass, biogas, geothermal, and natural gas displaces coal generation (Fig. 3.4B). New coal is not installed at carbon adders above \$40/tCO2 and, at \$70/tCO2, almost all existing coal plants are retired. Existing nuclear capacity continues operation under all carbon adders, but new nuclear generation appears in this power system only at carbon adders of \$70/tCO2 and above in the Base Cost scenario. Geothermal and biogas renewable baseload capacity are installed under all carbon adders to help satisfy RPS requirements.

Power system carbon emission levels equal 54% of 1990 emissions by 2030 in the Base Cost scenario at a carbon adder of \$70/tCO2. These emission levels are consistent with the 450 ppm climate stabilization target. In this low-carbon power system, new natural gas generation is installed as early as 2014 to replace retiring capacity (Fig 3.5A). The available geothermal and biogas resources are brought on early as an inexpensive way to help meet RPS targets. Wind generation is the primary technology that helps to meet increasing RPS requirements between 2018 and 2022, but generation from solid biomass also makes a contribution to RPS and decreased CO2 emissions in this timeframe.

Investment in solar does not begin until 2026 when falling PV costs and rising RPS demand make central station solar PV attractive. Solar PV comprises almost all capacity additions in the final investment period of 2026-2029. It should be noted that should solar PV costs decline faster than modeled in this scenario, this technology would be deployed more quickly and at a larger scale. Such cost trajectories have been proposed by the United States Department of Energy SunShot Initiative, which has the goal of reaching an installed overnight solar PV capital cost of \$1/Wp by 2020.

At a carbon adder of \$70/tCO2, non-baseload generation dominates the generation mix by 2030, with solar, wind, hydroelectric, and gas providing 11%, 15%, 18%, and 35% of generation respectively (Fig. 3.4B). While gas fuel costs increase between the third and fourth investment periods, the total amount spent on gas fuel decreases in the fourth period relative to earlier periods because solar displaces peaking natural gas generation (Fig. 3.5B). This power system contains 44 GW of central station PV capacity, which provides power during peak load hours, and 52 GW of onshore wind capacity, which provides power mostly during the winter, spring, and fall. In addition, 68 GW of hydroelectric and 100 GW of natural gas plants meet the remaining load and provide reserve capacity for the system. A plot of hourly power system operation is shown in Figure 3.6. Note that this power system contains substantially less baseload generation than is found in the present day WECC power system.

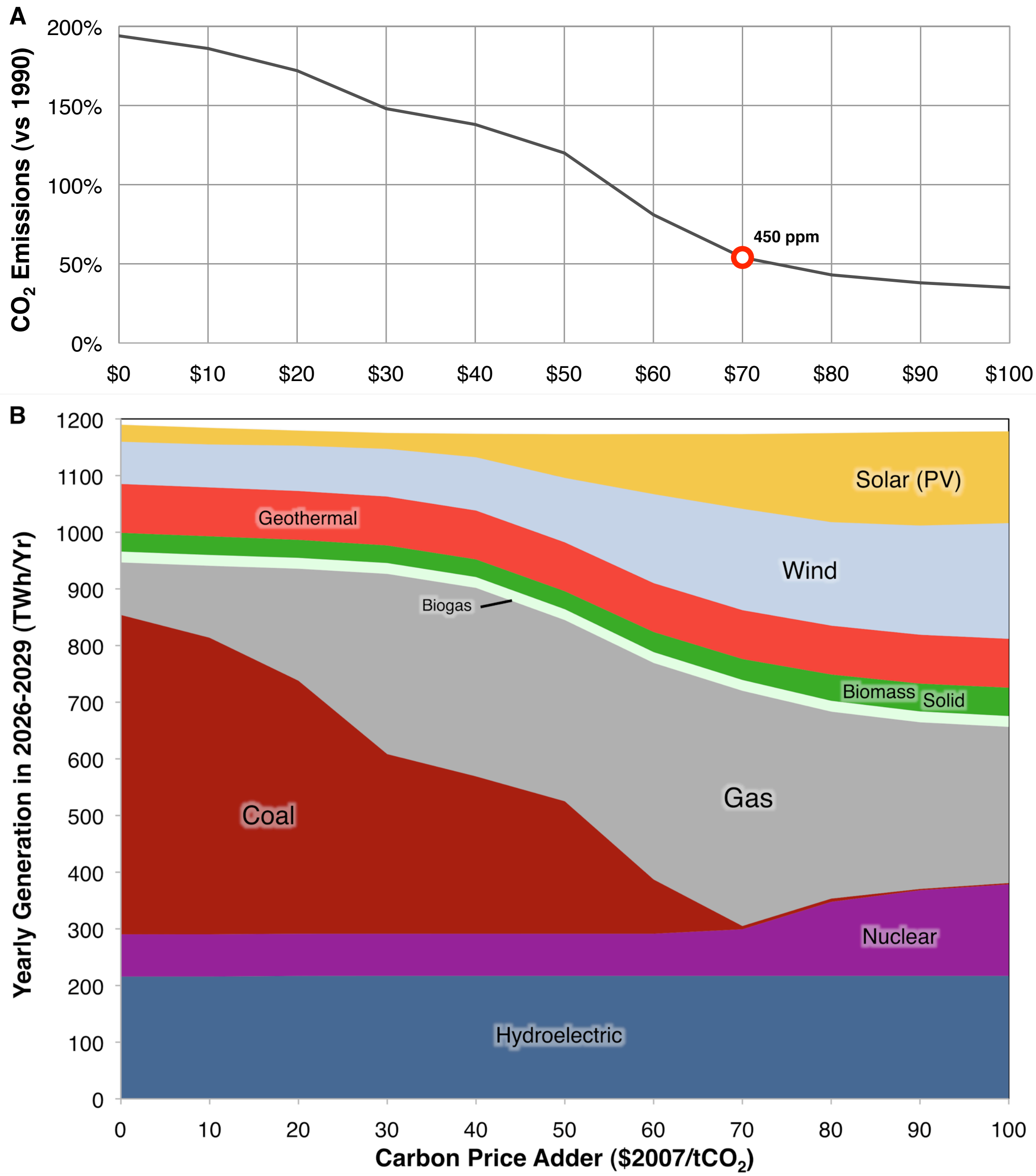


Figure 3.4 Base Cost scenario CO2 emissions relative to 1990 emission levels (A) and yearly power generation by fuel (B) in 2026-2029 as a function of carbon price adder. As shown in panel A, the climate stabilization target of 450 ppm is reached at a carbon price adder of $70/tCO2.

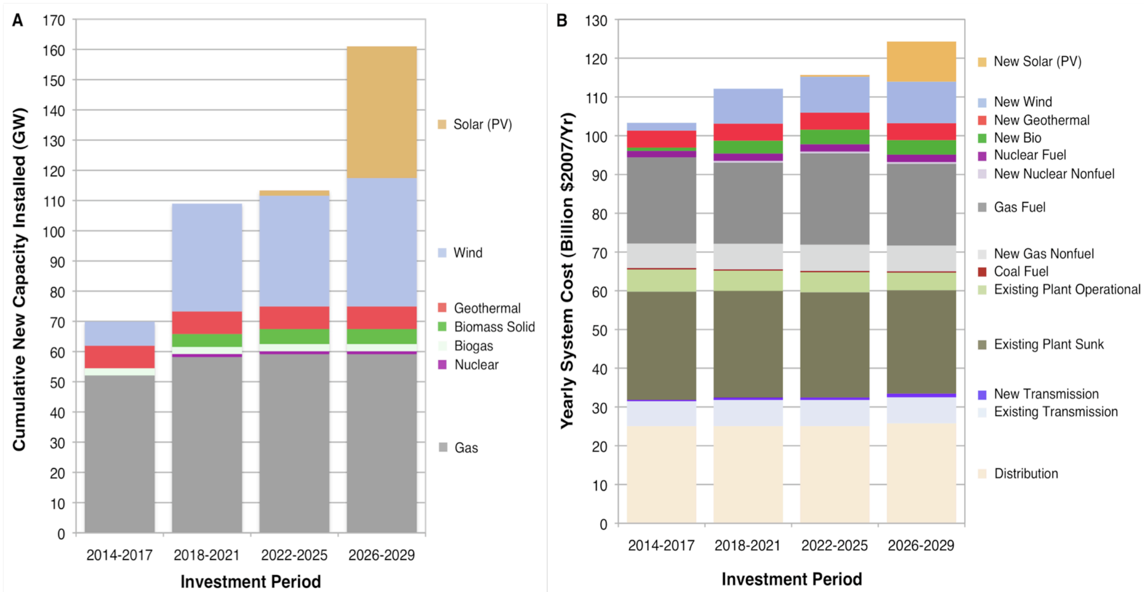


Figure 3.5. Base Cost scenario cumulative new capacity additions (A) and yearly average system costs (B) by investment period at $70/tCO2 carbon price adder. Nonfuel costs include capital, operations, and maintenance costs.

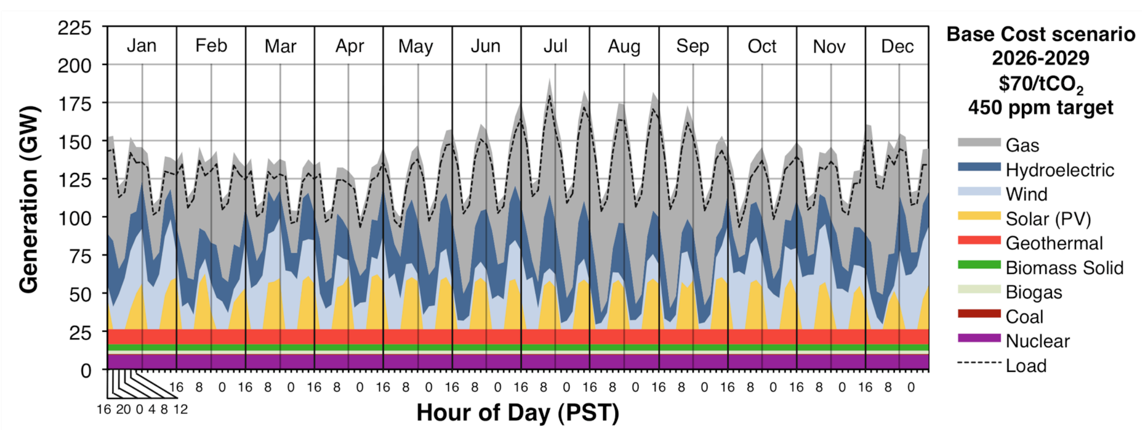


Figure 3.6 Base Cost scenario hourly power system dispatch at 54% of 1990 emissions in 2026-2029. This scenario corresponds to a $70/tCO2 carbon price adder. The plot depicts six hours per day, two days per month, and twelve months. Each vertical line divides different simulated days. Optimizations are offset eight hours from Pacific Standard Time (PST) and consequently start at hour 16 of each day. Total generation exceeds load due to distribution, transmission, and storage losses. Hydroelectric generation includes pumped storage when storing and releasing.

Figure 7 shows the geographic distribution of power production in 2026-2029. Solar and gas generation, which complement each other temporally as dispatched by the optimization (Fig. 3.6), are co-located in the Desert Southwest. Wind generation is largely sited in the Rocky Mountains. While the existing transmission network is used extensively, 9800 GW-km of new long-distance high-voltage transmission is also built, mainly to enable delivery of power from high-quality Rocky Mountain wind sites to load centers (Fig. 3.7). Installation of PV in 2026-2029 does not spur much new transmission investment, except for a new 1 GW transmission line to bring solar power from northern Nevada to the San Francisco Bay Area.

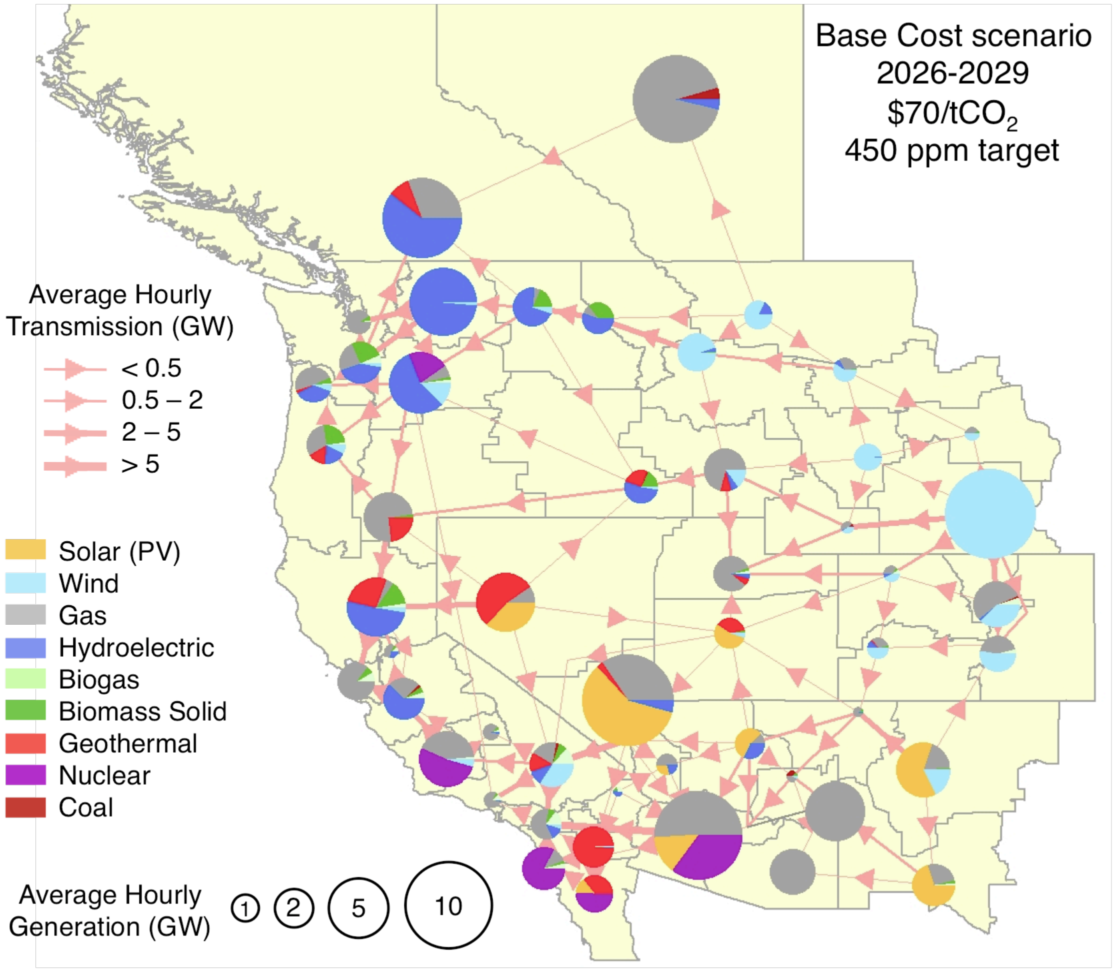
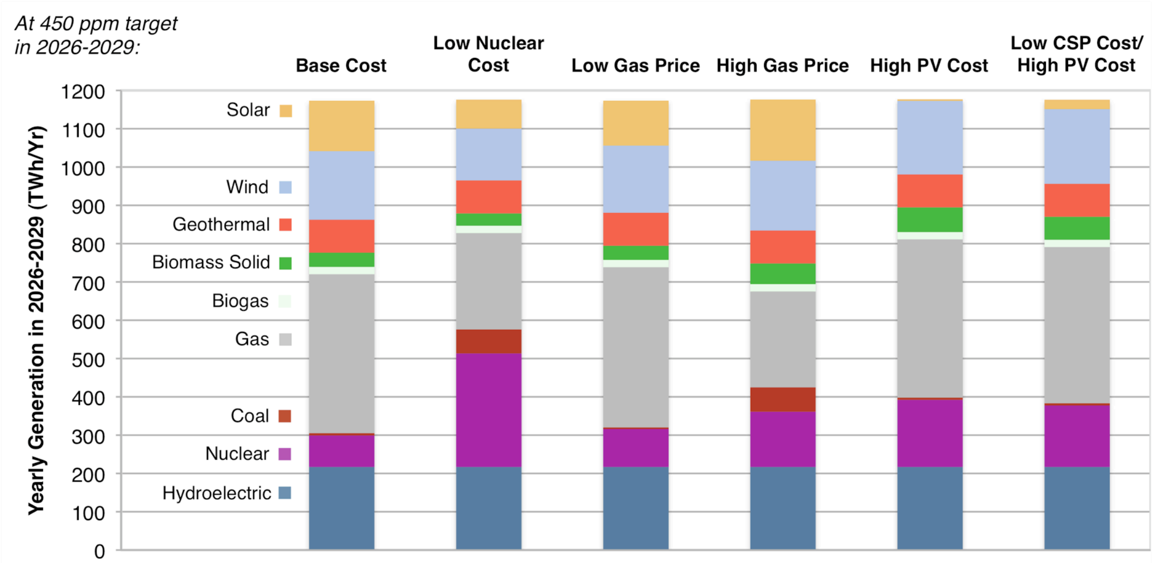


Figure 3.7 Average generation by fuel within each load area and average transmission flow between load areas in 2026-2029 at 54% of 1990 emissions for the Base Cost scenario. This scenario corresponds to a $70/tCO2 carbon price adder. Transmission lines are modeled along existing transmission paths, but are depicted here as straight lines for clarity. The Rocky Mountains run along the eastern edge of the map, whereas the Desert Southwest is located in the south of the map.



	Base Cost	Low Nuclear Cost	Low Gas Price	High Gas Price	High PV Cost	Low CSP Cost/ High PV Cost
Carbon price adder ($2007/t$CO_2$)	70	59	87	66	84	86
Power cost ($2007/MWh)	113	110	110	114	114	114
Cumulative new transmission built by 2030 (10^3 GW-km)	9.8	6.0	9.0	11.7	12.0	12.3

Figure 3.8 Yearly generation by fuel in 2026-2029 for all scenarios discussed in this paper at an emission level consistent with the 450 ppm climate stabilization target (54% of 1990 carbon emission levels by 2030). The carbon price adder, cost of power, and cumulative new transmission built at the 450 ppm climate stabilization target are also tabulated for each scenario in 2026-2029. Results in this figure are obtained by varying the carbon price adder for each scenario until the target emission level is reached.

Low Nuclear Cost Scenario

With carbon policy that reduces emissions below 1990 levels (285 MtCO2/yr) by 2030, the optimal power system design is highly responsive to the capital cost of nuclear. At carbon price adders of less than or equal to $50/tCO2, the Low Nuclear Cost and Base Cost scenarios are identical because no new nuclear is built under weak carbon policy in either scenario. As the carbon price adder is increased, the least-cost strategy for reducing CO2 emissions in the Low Nuclear Cost scenario relies on fuel-switching from coal to nuclear power.

Above $50/tCO2, new nuclear power appears in the Low Nuclear Cost scenario. In this scenario, the 450 ppm climate stabilization target of 54% of 1990 carbon emissions by 2030 is reached at a carbon price adder of $59/tCO2. A considerably different power system is designed relative to the Base Cost scenario due to the inclusion of large amounts of new nuclear capacity. The energy generated by nuclear in 2026-2029 is 25% of the total (Fig. 3.8), with an installed capacity of 37 GW – four times the current WECC-wide capacity of 9 GW. Solar, wind, hydroelectric, and gas plants provide the remaining generation above baseload, at 6%, 11%, 18%, and 21% of total electricity, respectively.

Of the six scenarios explored here, the Low Nuclear Cost scenario results in the smallest transmission build-out. A total of 6000 GW-km of new transmission capacity is installed, which is considerably less than the 9800 GW-km found in the Base Cost scenario. New nuclear plants are built at key junctions where existing transmission capacity is present but is underutilized due to the retirement of existing coal power plants. Hourly system operation is similar to that in present day, except with nuclear in the place of coal. In this scenario, nuclear and coal are found to be suitable substitutes. The strength of carbon policy determines which of these two large-scale baseload generation options should be installed on an economic basis.

Low Price Gas Scenario

Recent projections (U.S. Energy Information Administration, 2011b) suggest that natural gas prices may remain low in the future, a possibility that we explore in the Low Gas Price scenario. In this scenario, at the 450 ppm climate stabilization target, the 2030 optimal power system is very similar to that in the Base Cost scenario. In both scenarios, virtually all emissions originate from natural gas, with the share of generation from this fuel effectively constrained by the 450 ppm target. Due to the lower cost of natural gas in the Low Gas Price scenario, it takes a carbon price adder of \$87/tCO2 to reach the 450 ppm target in the Low Gas Price scenario, whereas in the Base Cost scenario only \$70/tCO2 is necessary. The difference in cost of natural gas generation resulting from the two natural gas price levels is roughly equivalent to that induced by a \$17/tCO2 difference in carbon price adder. As a result, similar generation fleets are deployed in the Base Cost and Low Gas Price scenarios.

High Gas Price Scenario

The High Gas Price scenario demonstrates that many other generation sources can substitute for natural gas if gas prices become high in the 2030 timeframe. To reach the 450 ppm climate stabilization target in this scenario, the reliance of the optimal power system on gas-fired generation is substantially decreased. Only 21% of power in the High Gas Price scenario is generated from gas, a 40% reduction relative to the Base Cost scenario. Low-carbon generation from new nuclear, biomass solid, wind, and solar displaces gas generation. In addition, instead of retiring virtually all existing coal plants as in the Base Cost scenario, some existing coal is kept online in the High Gas Price scenario, generating 5% of electricity and producing 31% of carbon emissions. The carbon price adder at which the target is reached in the High Gas Price scenario is \$66/tCO2, which is \$4/tCO2 lower than is found in the Base Cost scenario. In combination with the reduced overall emissions resulting from lower natural gas deployment, a lower carbon adder allows for the retention of existing coal in the optimal power mix in the High Gas Price scenario.

Solar Cost Scenarios
In all scenarios above, solar PV deployment is an important driver of lowering emissions by 2026-2029. The capital costs of this technology are assumed to decline substantially between present day and 2030 at a rate of 3.7%/yr, resulting in large-scale deployment in the last investment period. To explore the dynamics of a low-carbon power system without the availability of low-cost solar PV, we explore a scenario with a higher PV cost.

Despite continued capital cost reduction in the High PV Cost scenario (2.2%/yr), multi-GW-scale solar PV investment does not occur at 54% of 1990 carbon emissions by 2030, with just over 1 GW of capacity installed. Natural gas and solar are both peaking resources and are generally considered substitutes, but the 450 ppm target limits the total amount of gas generation in both the Base Cost and High PV Cost scenarios, effecting deployment of other types of generation instead. Relative to the Base Cost scenario, solar PV is replaced by a combination of nuclear, biomass solid, and wind power rather than natural gas.

In the Low CSP Cost/High PV Cost scenario, 9 GW of CSP parabolic trough systems without thermal storage are deployed in the Desert Southwest by 2030, generating 2% of WECC-wide electricity. These CSP plants preclude installation of PV generation, as the economics of CSP are favorable relative to those of central station PV in this scenario. CSP technology with thermal energy storage is not deployed. The Low CSP Cost/High PV Cost scenario is very similar to the High PV Cost scenario because the amount of CSP generation deployed in the former is small relative to system load.

In both of the solar cost scenarios, the 450 ppm target occurs at a power cost of \$114/MWh, \$1/MWh higher than is found in the Base Cost scenario. However, the carbon adder that makes the power system reach the target is found to be much higher at \$84-\$86/tCO2 relative to \$70/tCO2 in the Base Cost scenario.

Post-Optimization Dispatch Results
To ensure reliability, after each cost optimization, the performance of the proposed power system is tested using 16,800 distinct hours of data for each investment period. This check ensures that enough capacity has been built to serve load under conditions that were not included in the optimization stage. For this paper, a total of more than 4 million hours were simulated under all cost and carbon price adder scenarios discussed. Among these, no combination of cost scenarios and carbon price adders results in power shortages, even for a single hour or a single load area. The success of the dispatch check adds validity to the model's method of sampling median and peak load study hours to plan an electric power system with intermediate levels of intermittent renewable generation.

3.5 Discussion
To build an electricity sector consistent with a 450 ppm climate stabilization target, our results indicate that the RPS might be a logical first step that guarantees that renewable capacity is added in the near term. In advance of national or regional carbon-reduction

policies, RPS targets establish a policy environment that begins to decarbonize the energy mix. In our simulations, RPS policies effect reductions in emission levels primarily by promoting cost-effective baseload renewable technologies such as geothermal, biomass, and biogas in the near term. However, in a scenario with existing RPS and a carbon price adder of $0/tCO2 – a business-as-usual case – emissions from the lowest-cost western North American electric power system would be roughly double the 1990 levels by 2030 (Fig. 3.4B). Current RPS targets in western North America are not set high enough to put electric power sector emissions on track to stabilize the climate at or below 450 ppm (i.e. allow no more than 54% of 1990 emissions in 2030). To reduce emissions below 1990 levels by 2030, optimal power systems determined via SWITCH include more renewable electricity generation than is mandated by RPS targets.

We demonstrate that the ambitious 450 ppm climate stabilization trajectory can be achieved using a fleet of existing generation technologies. Across the scenarios investigated here, the composition of the fleet varies substantially but the resulting power systems also exhibit a number of commonalities. In all 450 ppm scenarios, no new coal-fired generation is added to the power mix as investment in carbon-intensive generation isn't consistent with long-term climate targets. Some existing coal is still operated until 2030 in scenarios with a carbon price adder below $70/tCO2, as its economics remain favorable relative to gas generation below this carbon price.

In most 450 ppm scenarios, virtually all emissions originate from gas-fired generation, with this fuel accounting for between 21% and 36% of total generation. At the upper bound of 36%, the amount of gas generation is effectively constrained by the 450 ppm target. Despite this upper bound on gas generation, the system appears to have sufficient flexibility to integrate between 17% and 29% of electricity from intermittent renewable generation cost-effectively in all scenarios using natural gas and hydroelectric resources. This is evident from the High Gas Price scenario in which the share of natural gas is the smallest, but the share of intermittent renewables is the largest of any 450 ppm scenario investigated (Fig. 3.8).

Electricity storage is not used extensively due to round-trip efficiency losses and high costs. For these reasons, battery storage, compressed air energy storage, and solar thermal systems with thermal energy storage are not installed at any carbon price adder in the scenarios discussed here. Existing pumped hydroelectric storage provides hourly arbitrage sparingly as there is sufficient lower-cost dispatchable generation already present. The inclusion of ancillary services to compensate for contingencies such as uncertain solar, wind, and load forecasts may add enough value to enable the addition of new storage projects to the optimal electric power system.

Given the large amount of system flexibility discussed above, wind and solar combined with natural gas and hydroelectric act as substitutes for baseload generation from biomass solid and nuclear. In this study of western North America, these technologies are acceptable substitutes on an operational basis within the levels of intermittent renewable penetration and carbon emissions explored. They are also substitutes on an economic basis as can be seen by their levels of deployment within the SWITCH cost optimization framework.

We find that achieving the 450 ppm target by 2030 has similar costs across the scenarios we investigate (Fig. 3.8). In the scenarios presented here, WECC-wide average power costs are between $110/MWh and $114/MWh. While the system receives modest cost benefits from low-cost nuclear or low-cost PV generation, neither of these technologies alone is integral to meeting the 2030 emissions target. The cost of achieving deeper emission reductions without nuclear in the Base Cost scenario would be only slightly higher relative to the Low Nuclear Cost scenario: about 3% higher to reach 54% of 1990 levels by 2030 (Fig. 3.8). This suggests that it is possible to build a reliable, low-carbon power system without nuclear power for similar costs to a nuclear-centered system. We also show that even if PV capital costs or natural gas prices are higher than projections in the Base Cost scenario, it is possible to achieve significant de-carbonization at only a slight cost premium. In both the High PV Cost and High Gas Price scenarios, at 54% of 1990 emissions by 2030, the increase in power cost is $1/MWh or 1% relative to the same emission levels in the Base Cost scenario.

In the scenarios presented here, the lowest-cost power system designed for a 450 ppm target occurs at a carbon price adder of between $59/tCO2 and $87/tCO2. While the carbon price adder in these scenarios may appear high, the actual cost increase to redesign the grid in order to achieve these deep emissions reductions is relatively low (Fig. 3.9), with a power cost increase of between 16% and 20% relative to scenarios without any carbon price adder (i.e. business-as-usual).

In addition to comparing scenarios consistent with a 450 ppm target, we investigate the cost of power in all six cost scenarios at different levels of carbon emissions. At all carbon emission levels above 40% of 1990 levels by 2030, the projected cost of power is found to differ by at most 5% between any pair of scenarios achieving similar decarbonization (Fig. 3.9). Further decarbonization beyond this point could be realized by replacing all the remaining coal power and much of the natural gas with renewables and/or nuclear power, but is not investigated in this study.

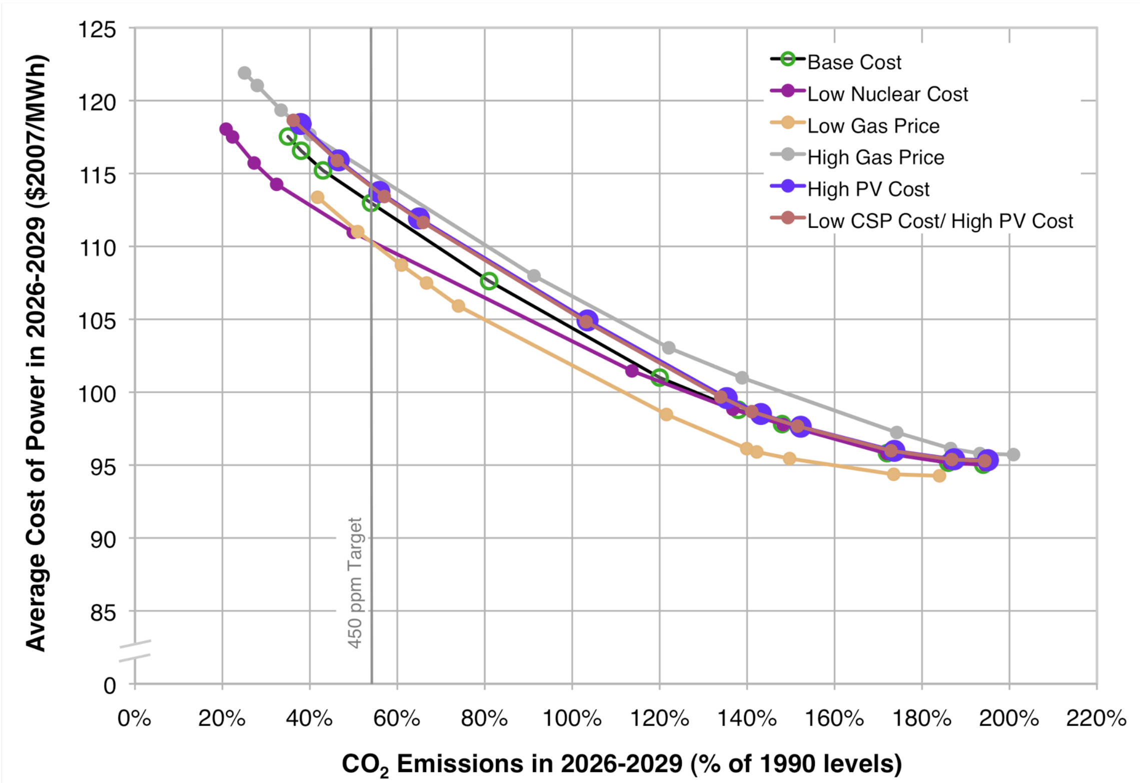


Figure 3.9 Average cost of power in 2026-2029 as a function of carbon emissions for all scenarios. Each point represents an optimization performed at a distinct carbon price adder, with the rightmost and leftmost points on each line representing optimizations at \$0/tCO2 and \$100/tCO2 respectively. Intermediate points range between these values in steps of \$10/tCO2. The broken y-axis allows for ease of comparison of the cost of power between scenarios but visually overstates the magnitude of power cost differences. For example, the Base Cost scenario power cost increases by only 18% when moving from the far right of this plot to the 450 ppm target line.

By optimizing capacity expansion and hourly generation dispatch simultaneously, SWITCH is uniquely suited to explore both the value of and synergies among various power system technology options, providing policymakers and industry leaders with important information about the optimal development of the electricity grid. Integrating long-term, coordinated generation, storage, and transmission planning improves the ability of the electric power sector to meet economic and climate goals. Analyses like this can help identify the least-expensive response to climate change, but concerted action will be needed to develop this system, such as ensuring that the cost of renewable technologies continues to decrease, securing low-cost financing for renewable power, and developing market structures that can accommodate changes in grid operation that will result from the deployment of low-carbon technologies.

3.6 Conclusions

This study illustrates realistic future grid scenarios with baseload, dispatchable and intermittent generation, transmission, and storage at minimal cost, taking into account the variability of renewable technologies. The least expensive power system studied, which implements current RPS policies but no further carbon policy, would deliver power at an average cost of $95/MWh, but would have roughly double the 1990 emission levels by 2030. Achieving emission levels of 54% of 1990 levels is shown to be possible by 2030 under a range of possible future costs and with many different combinations of low-carbon and conventional generation technologies. We find that intermittent renewable technologies can make an important contribution to emission reductions, comprising between 17% and 29% of total electricity generated by 2030 in scenarios consistent with the 450 ppm target. Despite differences in power mix due to the range of cost assumptions investigated in this study, the resultant power systems deliver power at similar costs. The carbon price to induce these deep carbon emission reductions is high, but the delivered cost of power increases by at most 20% over business-as-usual. High-resolution models like SWITCH make it possible to find low-cost solutions that challenge the assumption that the deployment of the low-carbon grid is very expensive.

3.7 Epilogue

We extended this work in California's Carbon Challenge Phase 1 (Wei, Nelson et al., 2012) to integrate Switch's electricity supply analysis with demand-side electrification and efficiency along with the transportation sector look at what it would take to meet 2050 goals. This was the first major demonstration of coupling the Switch model with external analysis and modeling efforts to develop a broader mitigation plan. Expanding the scope of analysis to other sectors was important because they have strong two-way interactions with central electricity planning via aggregate load, electricity prices and emission factors. Extending the timeframe to 2050 was important because many infrastructure components have lifetimes that extended beyond the end of the 2030 analysis. A 25-year analysis would not be able to fully assess the value of those investments and avoid stranded assets. For example, it was clear that a transition from coal to natural gas can meet near-term emission reduction goals, but it was unclear whether large amounts of natural gas infrastructure would be compatible with long-term goals or if it would become stranded assets. The same reasoning applies to distributed generation with combined heat and power plants that rely on fossil fuels, or transitioning the transportation fleet to natural gas.

Increasing the time duration of the study also enabled us to examine the impacts of prospective technologies to help us prioritize research, development and deployment goals. This type of study also lets us determine the time frame in which new technologies would become valuable and be deployed - for example, low- or zero-emission balancing assets such as storage or demand response have low value in the next few decades while weak carbon caps permit cheap natural gas to outcompete them, but become increasingly valuable in 2040 and 2050 when tight carbon caps limit the use of natural gas. This tells us we need to start developing those technologies now so that we can deploy them at scale in a few decades.

A major finding from that study was that no single course action was sufficient to meet emission targets; climate stabilization requires strong action on multiple fronts. Core action items were reducing supply-side emissions, deploying demand-side efficiency, and transitioning vehicles and heating from fossil fuels to electricity and biofuels. Beyond the core action items, we identified other action items that provided multiple pathways to achieve emission goals: behavioral changes for greater conservation, sequestration options to offset emissions or pushing harder on the core action items.

In California's Carbon Challenge Phase 2, Volume 1 (Wei, Greenblatt et al., 2013), summarized in (Wei, Nelson et al., 2013), we significantly extended the depth and breadth of the analysis, including a wider range of future scenarios, improved methodologies and datasets, options of deploying enough Biomass Energy with Carbon Capture and Sequestration to result in a net carbon negative power system, demand response, a more detailed examination of industry, etc. This produced qualitatively similar results that were more robust and specific than Phase 1. Volume 2 (Nelson, Mileva et al., 2014) provided additional detailed interpretation and documentation of the electricity supply side results.

These studies included detailed bottom-up projections of electricity demand that included various efficiency scenarios and added demand from electrifying vehicles and heating loads. An unanticipated finding was that increased efficiency and electrification shifts system peak from summer afternoons to winter nights, which shifts the relative value of solar and wind (Fig 3.10). Overall, we found multiple pathways that lead to a low-GHG future, all involving increased efficiency, electrification, and a dramatic shift from fossil fuels to low-GHG energy. We found the electric system had a diverse, cost-effective set of options, even with additional demand from electrification (Fig 3.11).

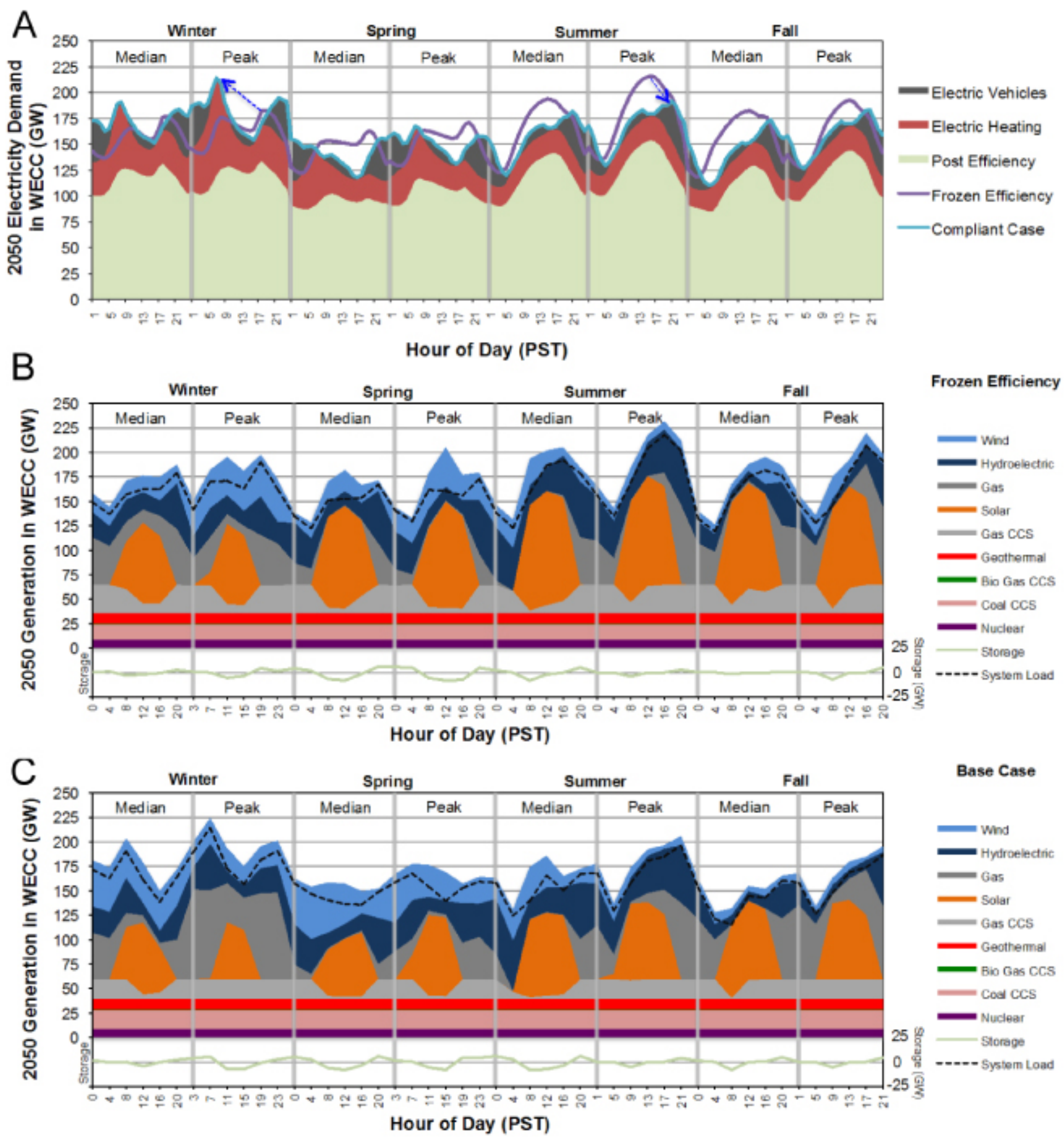


Figure 3.10 From Wei et.al. 2013. (a) Drastic shifts in load profile are seen from the implementation of efficiency ('post efficiency' scenario) and subsequent addition of loads from electric vehicles and heating. The compliant case ('Base Case') represents the load profile used as an input to the SWITCH model. One peak and one median demand day per season are shown in the figure for clarity, though the SWITCH model uses six days per season for each decadal time step. (b) WECC-wide electricity generation in 2050 as dispatched by SWITCH for the frozen efficiency load profile (c) WECC-wide electricity generation in 2050 as dispatched by SWITCH for the compliant case from figures 1(b) and 3(a). Note the shift from solar to wind power as the amount of efficiency and vehicle and heating electrification is increased from the frozen efficiency load profile.

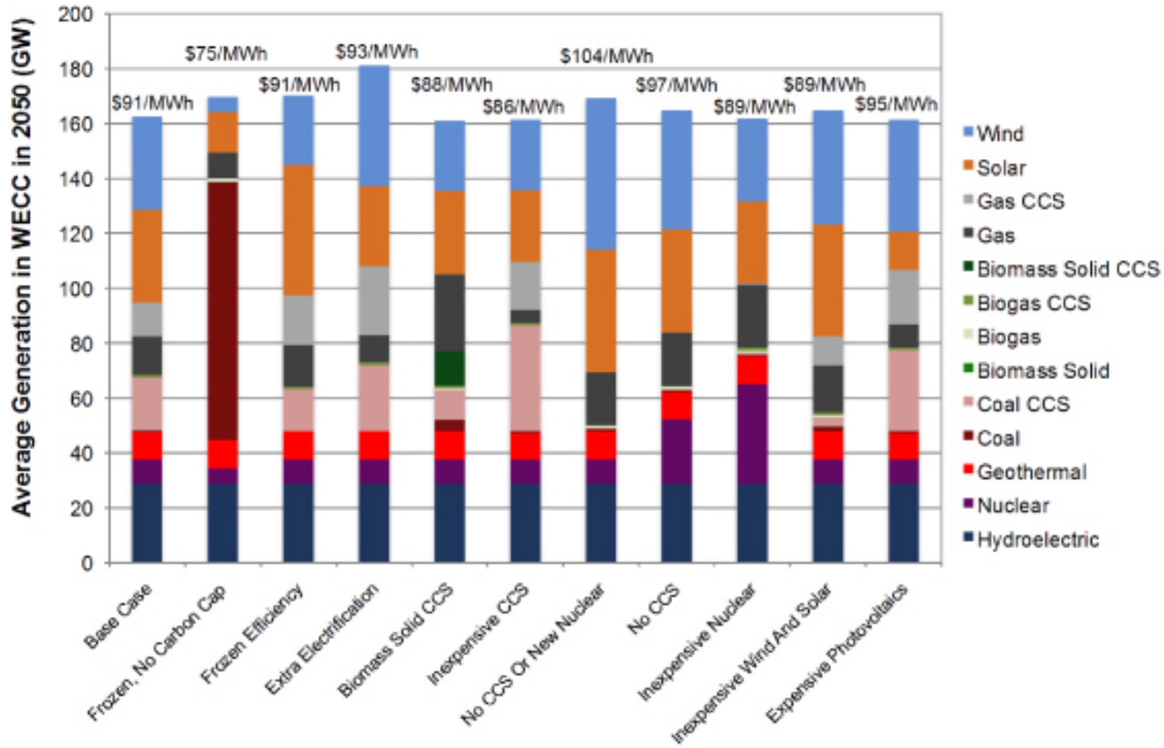


Figure 3.11 From Wei et.al. (2013). The projected delivered price of electricity in 2050 varies little across carbon-constrained scenarios, with the exception of a BAU scenario without emission constraints that uses large amounts of coal and a scenario that prohibits CCS and new Nuclear.

4 Evaluating value and impacts of green technologies

While planning low-carbon pathways and considering drivers of system costs in 2040 and 2050, we came to appreciate the need for developing new technologies now that can be deployed at scale in that timeframe to reduce costs and reduce risks. The following two collaborative studies provide detailed evaluations of low-cost solar (Mileva, Nelson et al., 2013) and Biomass Energy with Carbon Capture and Sequestration (Sanchez, Nelson et al., 2015).

Low-cost solar is an emerging reality as module costs have fallen dramatically since we began these studies. System integration requirements for solar are still challenging, especially if considering all of the investment decisions that could permit larger or smaller penetrations of solar. Switch is especially well-suited for this type of analysis because it develops a transitional pathway to a portfolio that allows our desired amounts of renewables and emission reductions. In low-cost solar study, we evaluated system-wide impacts and cost-effective solar penetration levels if SunShot cost targets are achieved. We also explored interactions with complementary technologies including demand response and cost breakthroughs in storage.

Biomass Energy with Carbon Capture and Sequestration (BECCS) is interesting because it provides electricity while withdrawing carbon from the atmosphere. The emission credits generated by this process could be extremely valuable after all lower-cost emission reduction methods are exhausted and we hit an inflection point on the carbon reduction supply curve. The emission story of BECCS is that most of the carbon that is withdrawn from the atmosphere by plants when they are growing is sequestered underground after they are combusted. As long cultivating and harvesting the biomass does not degrade ecosystem productivity or soil carbon cycles, the net emissions are negative. This work demonstrated that BECCS provides interesting and valuable opportunities that are worth investigating further, and that most of the value of BECCS in most situations comes from sequestration rather than energy. This also indicates that other sequestration strategies such as improved land management, biochar, or ecosystem restoration could be quite valuable, assuming we can work out the science.

4.1 SunShot solar power reduces costs and uncertainty in future low-carbon electricity systems

> The United States Department of Energy's SunShot Initiative has set cost-reduction targets of $1/watt for central-station solar technologies. We use SWITCH, a high-resolution electricity system planning model, to study the implications of achieving these targets for technology deployment and electricity costs in western North America, focusing on scenarios limiting carbon emissions to 80% below 1990 levels by 2050. We find that

achieving the SunShot target for solar photovoltaics would allow this technology to provide more than a third of electric power in the region, displacing natural gas in the medium term and reducing the need for nuclear and carbon capture and sequestration (CCS) technologies, which face technological and cost uncertainties, by 2050. We demonstrate that a diverse portfolio of technological options can help integrate high levels of solar generation successfully and cost-effectively. The deployment of GW-scale storage plays a central role in facilitating solar deployment and the availability of flexible loads could increase the solar penetration level further. In the scenarios investigated, achieving the SunShot target can substantially mitigate the cost of implementing a carbon cap, decreasing power costs by up to 14% and saving up to $20 billion ($2010) annually by 2050 relative to scenarios with Reference solar costs.

Introduction

The high cost of solar electricity technologies relative to conventional fossil fuel generation has been a barrier to their deployment at large scale. In 2011, solar generation provided less than 1% of electricity in the United States (U.S. Energy Information Administration, 2011a) and 3% in Germany(Fraunhofer Institute for Solar Energy Systems ISE, 2012). The solar photovoltaic (PV) industry has experienced fast-paced expansion in recent years, with annual growth rates in PV production of at least 40% since 2000 (Jäger-Waldau, 2012). Installed costs for PV declined by 43% between 1998 and 2010 (Barbose, Darghouth et al., 2011), but future cost and performance projections vary widely. In 2011, the United States Department of Energy (DOE) launched the SunShot Initiative, a comprehensive lab-to-market program that seeks to drive innovation and lower the cost of solar technologies, including PV and concentrating solar power (CSP). The cost target for PV is $1/W for central-station systems and $1.5/W for residential installations by 2020 ($2010) (US Department of Energy, 2012a).

The SunShot Vision Study(US Department of Energy, 2012b) provides an extensive analysis of the pathway to reaching the SunShot targets and implications for solar deployment in the United States. Similarly, we explore power system dynamics with SunShot solar costs, but, building on the SunShot Vision Study, we focus on scenarios with a carbon cap requiring the electricity sector to reduce its emissions to 80% below 1990 levels by 2050. This target is consistent with the Intergovernmental Panel on Climate Change's (IPCC) 450 parts per million (ppm) stabilization target for atmospheric concentration of carbon dioxide equivalent (CO2-e), which would limit planetary warming to 2°C above preindustrial levels (Intergovernmental Panel on Climate Change. Working Group 3, 2007). Several countries and states already have equivalent policy goals in place. The State of California has put into law a requirement to reduce greenhouse gas emissions (GHG) to 1990 levels by 2020 with Assembly Bill 32 (AB32) (California Air Resources Board, 2012). In addition, Executive Order S-3-05 calls for a further decline in the state's emissions to 80% below 1990 levels by 2050 (US Department of State, 2010). At the federal level, President Obama's administration supports the implementation of a cap-and-trade program to reduce GHG emissions to 83 percent below 2005 levels by 2050. In this work, we explore how the Western Electricity Coordinating Council (WECC) can achieve deep GHG emission reductions in the 2050 timeframe. WECC encompasses fourteen Western states, the Canadian provinces of Alberta and British Columbia, and the northern portion of Baja California, Mexico.

We use SWITCH, a capacity-planning model whose goal is to determine the most cost-effective investments in electric power grid infrastructure (Fripp, 2008; Fripp, 2012). SWITCH is a linear program (LP) whose objective is to minimize the cost of delivering power to load on an hourly basis subject to operational and policy constraints. The model uses time-synchronized hourly load and intermittent renewable generation data to determine optimal investment in and hourly dispatch of generation, transmission, and storage. We use a version of SWITCH developed for the electricity system of the entire WECC (Nelson, Johnston et al., 2012; Wei, Nelson et al., 2013). We choose to study the WECC power system because of its high-quality renewable resources that would likely make it a prime region for deployment of solar power. The WECC grid would also experience relatively high operational impacts associated with intermittent generation. This work investigates how the cost of solar technologies might affect both the ability of the WECC electricity sector to de-carbonize and the costs associated with reducing carbon emissions to the 2050 target.

Scenarios

All scenarios assume a WECC-wide carbon cap requiring the electricity sector to gradually decrease emissions each year to 80 percent below 1990 levels by 2050 (no banking or borrowing of emissions is allowed). In the Base Technology Scenario, we make nuclear and carbon capture and sequestration (CCS) technologies available to the SWITCH optimization. In the Limited Technology Scenario, we exclude nuclear and CCS from the potential generator fleet as technological availability in the 2050 timeframe is uncertain.

Within each of these scenarios, we explore two solar cost trajectories (Table 4.1.1) and compare the resulting power systems. In the SunShot cases, solar technologies achieve the targeted cost reductions by 2020 and then remain at these cost levels through 2050. In the Reference cases, solar generation remains more expensive, with costs decreasing gradually between present day and 2050. Finally, we investigate the role of flexible loads in the future WECC grid in the Flexible Load Scenario, which is based on the Limited Technology SunShot Scenario, but also allows a fraction of load in each hour to be shiftable, starting with 1 percent of load in the 2020 timeframe and reaching 10 percent of load by 2050.

Solar Technology	Year	Reference	SunShot
		2010$/W	*2010$/W*
Central PV	*2020*	2.51	1.00

	2030	2.40	1.00
	2040	2.20	1.00
	2050	2.10	1.00
Commercial PV	*2020*	3.36	1.25
	2030	3.21	1.25
	2040	2.95	1.25
	2050	2.81	1.25
Residential PV	*2020*	3.78	1.50
	2030	3.61	1.50
	2040	3.31	1.50
	2050	3.16	1.50
CSP 6 Hours of Storage[1]	*2020*	6.64	3.07
	2030	5.23	3.07
	2040	4.61	3.07
	2050	4.61	3.07
CSP No Storage	*2020*	4.60	2.50
	2030	4.20	2.50
	2040	3.90	2.50
	2050	3.50	2.50

Table 4.1.1 SunShot and Reference case costs by solar technology.

Costs for other technologies are based on Black and Veatch estimates and projections (Black & Veatch, 2012), and can be found in the Supporting Information. Natural gas and coal prices are based on the U.S. Energy Information Administration's Annual Energy

[1] In the *SunShot Vision Study*, CSP is modeled as having 14 hours of storage in the SunShot scenario. Currently, SWITCH only includes CSP with 6 hours of thermal storage, so the cost for CSP with 6 hours of storage in SWITCH is calculated based on the difference between CSP with 14 hours of storage and CSP with 11 hours of storage in the *SunShot Vision Study*, assuming costs increase linearly for each additional hours of storage. The cost for CSP with no storage is then calculated by assuming the same yearly cost-declination rate from present-day costs as for CSP with 6 hours of storage.

Outlook (US EIA AEO) 2011 Reference Case projections (US Energy Information Administration, 2011)

Model Description

The version of SWITCH used here minimizes the cost of producing and delivering electricity using a combination of existing grid assets and new generation, transmission, and storage. New capacity can be built at the start of each of four "investment periods," representing 2015-2025, 2025-2035, 2035-2045, and 2045-2055. Throughout this manuscript, we also refer to the four investment periods as 2020, 2030, 2040, and 2050 respectively. The investment decisions determine the availability of power infrastructure to be dispatched in each "study hour," sampled from a year of hourly data for each period. Investment and dispatch decisions are optimized simultaneously.

Study hours are initially sub-sampled from the peak and median load day of every month. Every fourth hour is selected, and dispatch decisions are initially made for (4 periods) x (12 months/period) x (2 days/month) x (6 hours/day) = 576 study hours for the entire study. As the main SWITCH optimization uses a limited number of sampled hours over which to dispatch the electric power system, dispatch verification is performed at the end of each optimization to ensure that the model has designed a power system that can meet load reliably. In this verification, investment decisions are held fixed and new hourly data for two full years are tested in batches of one day at a time. For the scenarios investigated here, several optimization iterations were performed until capacity shortfalls were eliminated from the dispatch verification, each iteration including the hour with the largest capacity shortfall from the previous iteration as well as five more hours for that day, spaced evenly four hours apart. Like the main SWITCH optimization, the dispatch verification enforces transmission constraints as a transportation network only rather than power flow, and does not include generator ramping constraints, and security constraints.

We use time-synchronized hourly profiles for load and renewable output to account for correlation between demand and renewable generation. Building on our prior work,12 for this study we have implemented a series of enhancements to SWITCH's treatment of generator types in order to simulate system operations as realistically as possible, at an unprecedented resolution for a capacity-expansion model of a large geographic area. Six categories of generators are operated: baseload, flexible baseload, intermediate, peaker, intermittent, and storage. For this work, we have implemented 1) flexible baseload operation for coal plants, which run around the clock but are allowed to ramp up and down on a daily basis, incurring a heat rate penalty when operating below full load, 2) intermediate operation for combined cycle gas generator turbines (CCGTs), which can vary output hourly, but incur costs and emission penalties when new capacity is started up and heat rate penalties when operating below full load, and 3) startup costs for peaker plants, which have flexible output restricted only by installed capacity. Additional model capabilities implemented as part of this study include: operating reserve requirements (spinning and quickstart), flexible loads, a carbon cap constraint, state distributed generation policy goals, and natural gas price elasticity.

A complete formulation of the version of SWITCH used in this study is available in the Supporting Information and at http://rael.berkeley.edu/switch/.

Results

Base Technology Scenario

In the *Base Technology Scenario*, we allow SWITCH to build new nuclear capacity as well as coal- and gas-fired plants equipped with CCS.

With *Reference* solar costs (Figure 4.1.1A), natural gas generation constitutes most capacity additions in the near term and begins to displace coal as the carbon cap becomes more stringent over time. If natural gas prices were to remain as currently projected and carbon policies were implemented, this fuel would likely play a dominant role in the WECC power system in the next two decades. By 2030, natural gas plants generate 46% of the total WECC energy, while wind and PV produce 12% and 7% of generation respectively. Geothermal (5%) and a small amount of biogas (1%) help meet the renewable portfolio standards (RPS) in WECC states with such policies in place.

In the *SunShot* case (Figure 4.1.1B), the availability of low-cost solar delays the deployment of low-carbon baseload capacity. In the *Reference* case, new geothermal installations provide 5% of energy in the 2030 timeframe to help meet the RPS and carbon cap requirements. By contrast, the *SunShot* case sees geothermal energy use at levels less than 1% before 2040. Similarly, CCS deployment is deferred: with *Reference* solar costs, coal CCS first appears in the power mix as early as 2030, providing 2% of energy in that timeframe; in the *SunShot* case, CCS installations are negligible through 2050. Delaying the need to deploy these technologies would allow for additional time to gauge their feasibility and costs, and to improve their performance.

By displacing natural gas and the associated emissions, large-scale solar deployment could allow the system to remain within the cap even without other low-carbon resources. Relative to the *Base Technology Reference Scenario*, the share of solar energy increases from 7% to 24% in the 2030 timeframe. Instead of intermediate and peaker gas generation, PV, whose output exhibits a positive correlation with the WECC demand profile, helps meet the daily peak load.

By 2050, the carbon cap induces transformative changes in the power mix. The need to reduce emissions limits the amount of natural gas in the system, lowering its energy share to 11% in the *Base Technology Reference Scenario*. Instead, a combination of low-carbon resources helps to meet load. Solar and wind provide 15% and 29% of energy respectively. Nuclear, geothermal, biopower, and coal CCS make up the balance of generation at 21%, 7%, 1%, and 2%, providing low-carbon baseload power. Hydro generates 15% of energy, and storage also plays a role with 5 gigawatts (GW) of new capacity in the WECC.

In the *Base Technology SunShot Scenario*, the penetration of intermittent renewable energy is even higher. Solar generates 31% of energy and wind's share is 24% in the 2050 timeframe. Natural gas provides 9% of energy and is an important source of flexibility. Hydro also helps balance renewables and generates 15% of energy. In addition, 27 GW of storage are installed throughout the WECC, about 5% of total system capacity and more than five times the new storage capacity in the *Reference* case. Geothermal provides 6% of electricity, and the share of nuclear is 13%. Relative to the 2030 dynamics, the trade-off between solar and natural gas is less prominent in the 2050 timeframe because the amount of natural gas is limited by the carbon cap rather than by fuel costs. Instead, the solar resource in the *SunShot* case displaces mostly nuclear energy relative to the case with *Reference* solar costs.

<u>*Limited Technology Scenario*</u>

In addition to technical issues around waste disposal and reactor safety, nuclear power today faces cost and public acceptance challenges. To date, CCS has not been deployed at scale and many CCS system components are still in the research, development, and demonstration phase. To explore a future in which low-carbon baseload power like nuclear and CCS is not readily available in a carbon-constrained system, we remove these technologies from the set of investment options in the *Limited Technology Scenario* and re-run the optimization with both *Reference* (Figure 4.1.1C) and *SunShot* (Figure 4.1.1D) solar costs.

In this scenario, the power mix remains similar to that in the *Base Technology Scenario* until the last investment period. However, as the carbon cap becomes more stringent over time leading up to the 2050 goal, the system changes substantially between the two. Without nuclear power and CCS technology – and with solar costs remaining high in the *Limited Technology Reference Scenario* – the power system relies on large-scale deployment of wind energy in order to meet the cap. Wind deployment expands in the last investment period: more than 200 GW of wind power are in operation by 2050, providing 42% of energy in the 2050 timeframe. The share of solar energy is 20%. About 11 GW of storage are also installed.

When SunShot targets are reached, both solar and wind generation increase relative to the *Base Technology SunShot Scenario* to make up for the lack of nuclear and CCS, reaching 34% and 30% respectively by 2050. The balance of generation remains similar across scenarios: geothermal provides low-carbon baseload energy while hydropower and gas generation contribute to both the energy and flexibility needs of the power system.

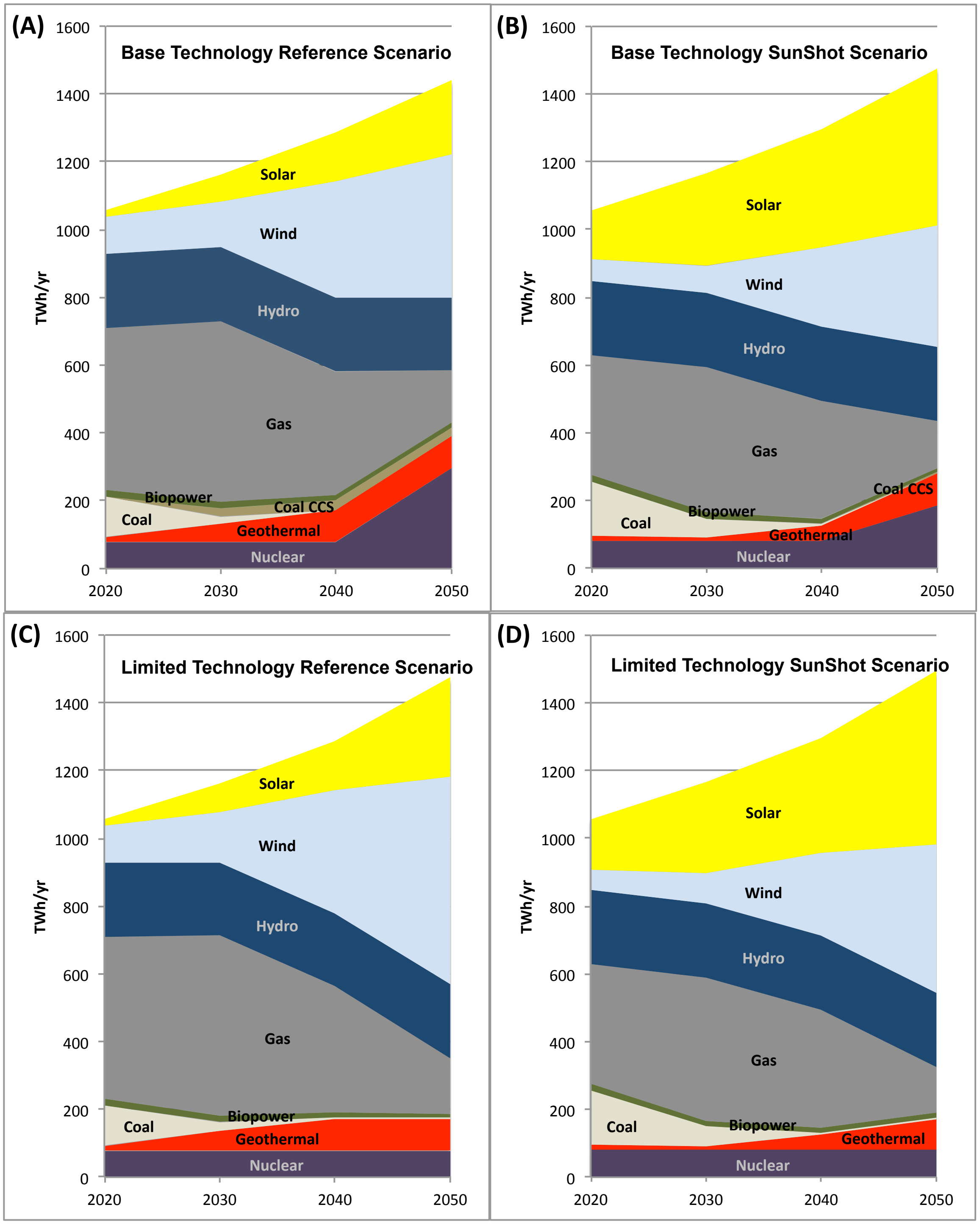


Figure 4.1.1 Energy mix by fuel and investment period.

<u>*Cost of Power*</u>

The cost of power increases over time across scenarios (Figure 4.1.2). However, SunShot solar availability contributes to a decline in cost relative to the *Reference* solar cost cases. In the last investment period in the *Base Technology Scenario*, the cost of power is $123/MWh with *Reference* solar costs and $112/MWh with *SunShot* solar costs. The difference is even more pronounced when nuclear and CCS technologies are unavailable to help meet stringent carbon targets in the 2050 timeframe. In the *Limited Technology Scenario*, the average cost of power rises to $129/MWh by 2050 with *Reference* solar costs. If the SunShot target is reached, the cost of power is $114/MWh.

Achieving SunShot targets mitigates the cost of carbon reductions in the WECC. While meeting the 2050 carbon cap appears possible with or without SunShot technology, when solar costs remain as in the *Reference* case, the cost premium for reaching the carbon target is 10% in the *Base Technology Scenario* and 14% in the *Limited Technology Scenario* in the 2050 timeframe. In the *Base Technology Scenario*, SunShot solar costs contribute to a decline in power costs in the medium-term timeframe. Only in the final decade of the simulation does the cost of power begin to rise relative to costs in the first investment period.

If SunShot solar is unavailable in the 2050 timeframe, the lack of nuclear and CCS in the *Limited Technology Scenario* increases the power cost by an additional 5% above the cost in the *Base Technology Scenario*. In contrast, when the SunShot targets are achieved, removing low-carbon baseload from the set of investment options increases power cost by only 1%, thus mitigating the risk associated with nuclear and CCS.

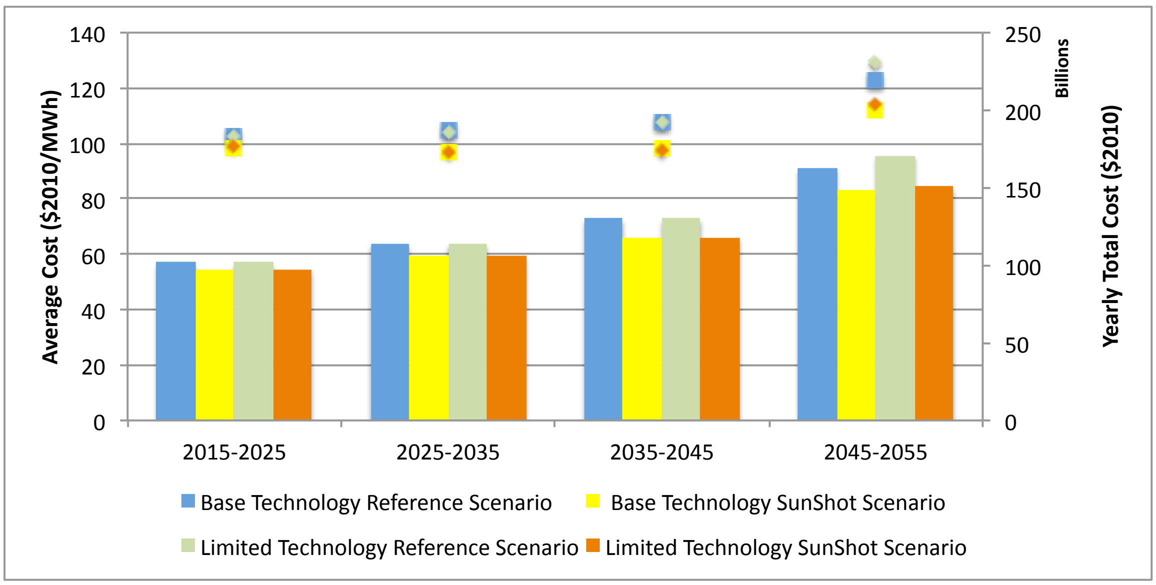


Figure 4.1.2 Yearly total cost of power (columns, left axis) and average cost of power (points, right axis) in the WECC in each of the four investment periods in the Base Technology Scenario and Limited Technology Scenario with and without SunShot solar costs. All costs are specified in real terms indexed to the reference year 2010. During the optimization, a real discount rate of 7% is used, so that costs incurred earlier in the study are weighed more heavily.

Infrastructure Deployment

Realizing the benefits of SunShot would require large build-out of solar capacity and new transmission in western North America (Figure 4.1.3). In the *Limited Technology SunShot Scenario*, PV is installed throughout the WECC, with large capacities built in the Desert Southwest but also in places with lower solar insolation including Alberta, Montana, Oregon, and Wyoming, among others. Transmission expansion is also necessary to bring the solar resources to the load centers. In the *Limited Technology SunShot Scenario*, 28,000 GW-km of new high-voltage, long-distance transmission are installed by 2050. However, the most new transmission – more than 50,000 GW-km – is built in the *Limited Technology Reference Scenario*, largely due to higher levels of wind power deployment in Montana, Wyoming, and Colorado, requiring long transmission lines to bring the wind energy to the load centers. For comparison, the existing transmission capacity input into SWITCH is approximately 71,000 GW-km.

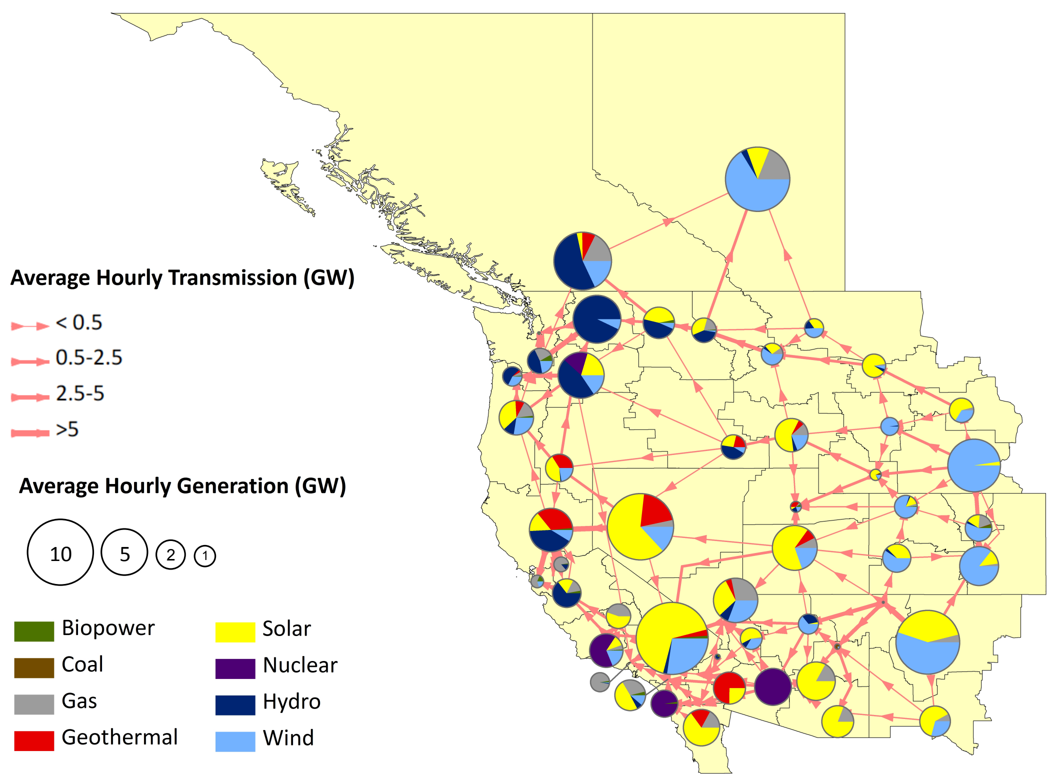


Figure 4.1.3 Map of generation and transmission in the Limited Technology SunShot Scenario.

PV capacity increases gradually over time, reaching 96 GW of central-station installations in 2030 and 185 GW in 2050 in the Limited Technology SunShot Scenario. Assuming PV array power density of 48 W_{DC}/m^2 for 1-axis tracking systems, (Denholm and Margolis, 2008) this would require close to 400,000 hectares (ha) or roughly 0.08% of the land area of the WECC. Central-station solar and wind power plants face permitting, environmental, and transmission-access challenges, which may be a barrier to

GW-scale deployment of these technologies. Renewable generation sites should be selected to minimize impacts on environmentally or culturally sensitive areas. The availability of multiple low-cost and low-carbon technologies could mitigate the siting risk associated with any one of them.

In the 2050 timeframe, 5 GW of CSP with 6 hours of storage are also installed, largely in California. As SWITCH does not yet model CSP with longer storage duration nor does it have decision variables for CSP storage dispatch[2], these results likely underestimate the economic potential of CSP were it to reach the SunShot cost targets. CSP with 12 to 14 hours of storage could provide dispatchable power around the clock, increasing system flexibility and providing important value not captured here (Denholm, Wan et al., 2013). However, the water requirements of CSP plants using evaporative cooling may be a limiting factor in its deployment as water is scarce in the WECC region.

More than 6 GW of distributed PV capacity are also deployed in the WECC in the Limited Technology Scenario. This deployment is driven by local incentives already in place such as the California Solar Initiative, which SWITCH enforces. Beyond existing subsidies, distributed PV is outcompeted by less expensive central-station PV in the model's cost-optimization framework. Distributed PV may have net benefits for the distribution network not captured by SWITCH (Piccolo and Siano, 2009). As a large-scale capacity-planning model, SWITCH also does not capture the set of decisions and market dynamics that may drive distributed PV adoption regardless of cost, including a complicated and geographically varied range of policies, incentives, retail rate structures, and individual preferences[3].

The scenarios presented above assume annual load growth of 1% as projected by the Energy Information Administration (US Energy Information Administration, 2010). Implementing additional energy efficiency measures and reducing the amount of load that needs to be served could greatly decrease the capacity build-out required to serve load reliably. For example, if technology assumptions were as in the Limited Technology SunShot Scenario but load were to remain at current levels (0% annual load growth), wind and solar capacity requirements would be cut in half and annual power system costs would be reduced by close to $60 billion annually or more than 40% by 2050. The value of energy efficiency will vary depending on the cost of generation available to meet load. Estimating the energy efficiency potential and costs is an important area of research

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[2] The dispatch pattern for each CSP project is parameterized and input into the optimization ahead of time as an hourly capacity factor.

[3] Other capacity-expansion models, including the Energy Information Administration's National Energy Modeling System (NEMS) (see http://www.eia.doe.gov/oiaf/aeo/overview/) and the Regional Energy Deployment System (ReEDS) at the National Renewable Energy Laboratory (NREL) (see http://www.nrel.gov/analysis/reeds) have similar limitations. The Solar Deployment System (SolarDS) model was specifically developed at NREL to project distributed PV adoption rates and has been used to create inputs to planning models. The SunShot Vision Study used SolarDS to estimate distributed PV penetration and input these levels into ReEDS before simulating the rest of the electric power system. SolarDS estimated 121 GW of distributed solar deployment in the United States by 2030 and 240 GW by 2050 with SunShot solar costs.

because investing in efficiency may be a cost-effective alternative to deploying generation capacity.

System Dispatch

With intermittent renewable penetration reaching 64% in the Limited Technology SunShot Scenario, the power system faces operational challenges, which are evident from the aggregate dispatch of the WECC power system in 2050 as optimized by SWITCH (Figure 4.1.4A). Significant system flexibility is required in the early evenings when solar generation ramps down earlier than load, resulting in a need for a steep up-ramp to follow the net load (load minus intermittent generation). In SWITCH's simulations, these net-load ramps are handled by a combination of hydro, storage, and intermediate and peaker gas generation. Combined-cycle gas plants are frequently operated at part load, gas combustion turbines are started up and cycled down as needed, and the existing flexibility from hydropower as well as pumped hydro storage is used extensively. In addition, multi-GW-scale deployment of new storage occurs by the last investment period, comprising 6% of system capacity in the 2050 timeframe.

As the least expensive storage option in SWITCH, almost all of the new storage is compressed air energy storage (CAES), with more than 29 GW installed throughout the WECC[4]. About 3 GW of battery capacity are also deployed. Storage deployment occurs in wind regions such as Colorado and Wyoming (~ 1 GW deployed in each), but most is built in the Desert Southwest to help handle the evening solar down-ramp. This is apparent from the dispatch pattern of storage (Figure 4.1.4A), which tends to charge during the peak load hours in the middle of the day – when solar generation is also peaking and net load is low – and discharge in the evening when the sun goes down but load does not decline as rapidly and net load is high. Storage dispatch is different from present-day patterns of charging during the night when demand and prices are low and discharging at peak when prices increase. Notably, storage is less active during the times when the most energy is spilled (the median load day in March in this simulation) as prices stay low throughout the day and little opportunity for arbitrage exists (SWITCH does not currently model seasonal storage). Energy is spilled in the spring and early summer when both the solar and wind resource are abundant while load is low throughout the day.

Like storage, load flexibility could contribute to system reliability and lower system costs. We investigate system dynamics in one additional scenario – the Flexible Load Scenario – that has the same technological availability assumptions as the Limited Technology SunShot Scenario, but includes the ability to shift loads within each day of the optimization. Specifically, we assume that 1% of load in each hour will be shiftable in 2020, 4% in 2030, 7% in 2040, and 10% in 2050. We give SWITCH the option to shift load to any hour within the day without cost or efficiency penalty.

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[4] CAES is a hybrid gas-storage technology as it combines underground reservoirs to store compressed air with a gas turbine. CAES is assumed to be sited in aquifer geology and widely available.

Flexible loads are shifted toward the solar peak when an abundant low-cost and low-emission resource is available, and away from the evening net-load peak (Figure 4.1.4B). The share of solar in the energy mix rises to 37% while storage deployment is reduced to 18 GW (from 34% and 29 GW respectively). The average cost of power in 2050 is $108/MWh, 5% lower than in the Limited Technology SunShot Scenario. This benefit would have to be compared against the cost of load flexibility programs.

SWITCH does not yet model a number of power system services such as automatic generation control (AGC), sub-hourly load following, inertial response, or primary contingency reserve (frequency response), currently incorporating only secondary contingency reserves (spinning and quickstart). In the results presented here, very little thermal generation is dispatched during certain times of the year, e.g. almost no gas generation is operated in May and June. The ability of the power system to maintain frequency after a contingency without traditional synchronous generators is a current research topic. While wind (Miller, Clark et al., 2011), solar (Zarina, Mishra et al., 2012), high-power storage technologies (Delille, Francois et al., 2012) and flexible load (Callaway and Hiskens, 2011) may be able to provide similar response, additional constraints may have to be incorporated into capacity-planning models such as SWITCH to ensure that the simulated system can operate reliably.

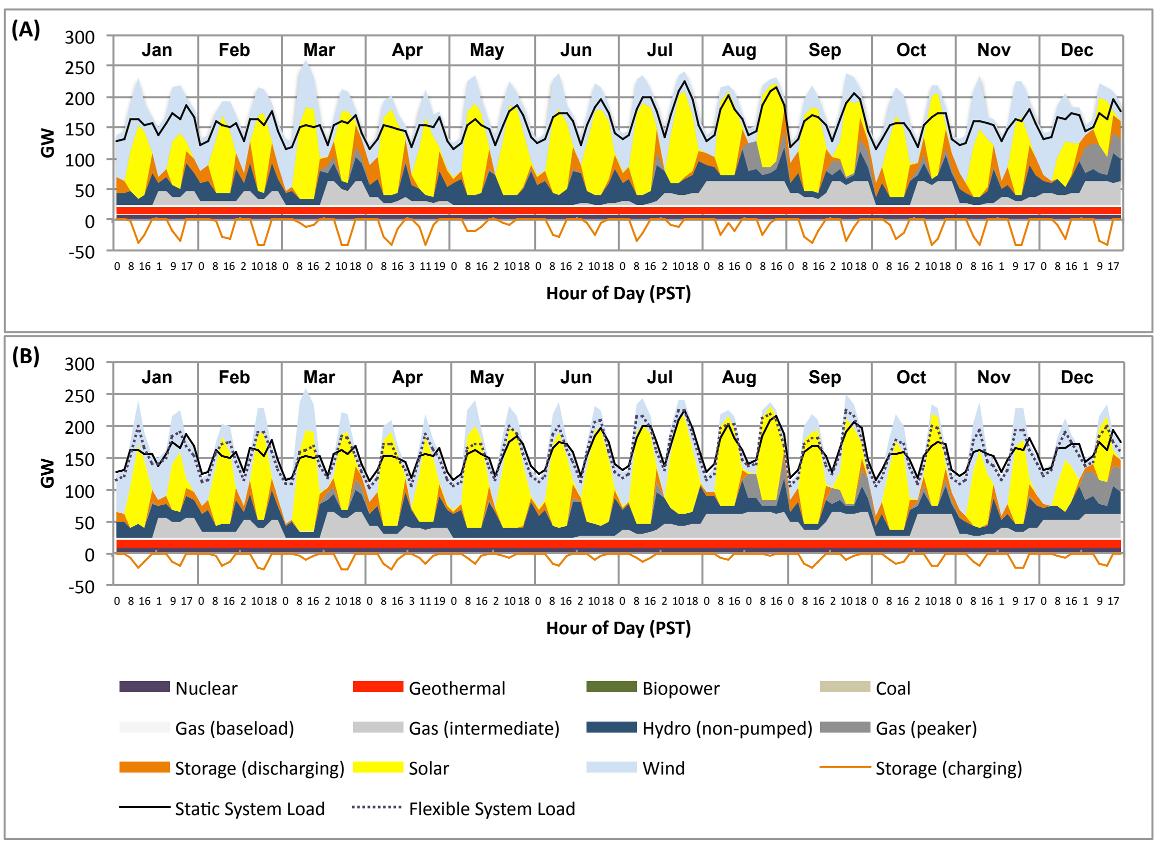


Figure 4.1.4 System dispatch in 2050 in the (A) Limited Technology SunShot Scenario and (B) Flexible Load Scenario. Total generation exceeds system load because of

transmission, distribution, and storage losses as well as curtailment of generation on resources.

Discussion

Achieving the SunShot target could make it cost-effective for solar power to provide more than a third of electricity in the WECC by 2050, aiding the ability of the WECC power system to reduce emissions while meeting load. Flexible load availability could increase this penetration level by moving additional load to the solar peak. While not included here, changes in the load profile such as from energy efficiency measures, inflexible nighttime charging of electric vehicles, or heating electrification could have the opposite effect (Wei, Nelson et al., 2013).

Without low-cost solar energy, the WECC power system relies on low-carbon baseload technologies to achieve the 2050 emission goals: in the Reference Base Technology Scenario, 27 GW of new nuclear and 4 GW of coal CCS capacity are built. If low-carbon baseload technologies are available, the cost to meet the 2050 carbon cap increases by 10% if the SunShot targets are not reached, a cost premium of $14 billion annually in the 2050 timeframe. If nuclear and CCS are not available, SunShot solar can substantially mitigate the cost increase from implementing a strict carbon cap, saving 14% or more than $20 billion annually by 2050. By comparison, the proposed budget for the SunShot program is $310 million for FY2013 (Department of Energy, 2012). Achieving the SunShot target could decrease electricity prices in the medium term and provide key benefits by containing power costs even as stringent de-carbonization of the power sector is implemented, potentially facilitating the passage of climate policy. While not included here, possible further cost declines beyond the SunShot target would imply even larger savings.

When SunShot solar is available, removing nuclear and CCS from the investment portfolio does not result in a sharp increase in costs. Achieving the SunShot target might therefore have the additional benefit of serving as insurance against the risk associated with relying on nuclear power and CCS for emission reductions. Delaying the need to deploy those technologies would also allow time for the R&D, innovation, and technological progress to make them a viable, cost-effective alternative for climate change mitigation.

We find that the 2050 emissions target can be achieved in the WECC electricity sector with or without SunShot solar power. Even if SunShot-level technological improvement is not achieved, however, it may still be cost-effective for solar as well as wind generation to make a significant contribution to energy supply in future low-carbon systems. Of the scenarios presented here, the lowest combined energy penetration level for these two intermittent technologies in 2050 is 44% (29% for wind and 15% for solar in the Base Technology Reference Scenario), a deployment level that will likely require changes to system operations and additional system flexibility resources.

SWITCH incorporates many elements of system dispatch in a capacity-expansion modeling framework and offers some of the most detailed treatment to date of day-to-day operations in an investment model. The SWITCH results presented here indicate that a range of system flexibility resources, including flexible gas-fired generation, hydroelectric generation, storage, and load response, can help to integrate large amounts of intermittent energy resources into the WECC power system. While technology availability may not be a limiting factor in achieving deep emission reductions with wind and solar, well-designed market mechanisms and policy structures may need to be put in place – in addition to long-term policy support for climate goals – to ensure coordinated investment in R&D and infrastructure, and efficient deployment of enabling technologies such as storage, demand response, flexible transmission, and active controls. It is important to continue investigating how to design a comprehensive strategy to create a least-cost, low-carbon electricity supply system.

Technological breakthroughs such as SunShot could potentially transform the WECC power system and mitigate the cost of emission reductions and the risk of failing to meet the 2050 climate goals. Achieving SunShot costs for solar technologies would require significant technological progress and a supporting policy framework: an increase in the solar industry's manufacturing capacity, streamlined permitting and siting for new plants and transmission lines as well as appropriate markets, policy, and operational practices. Provided strategic long-term planning is put in place, SunShot solar power appears poised to play a crucial role in containing electricity costs even as aggressive carbon emission reduction goals are achieved.

4.2 Biomass Enables the Transition to a Carbon-Negative Power System Across Western North America

Sustainable biomass can play a transformative role in the transition to a decarbonized economy, with potential applications in electricity, heat, chemicals, and transportation fuels (Demirbaş, 2003; Farrell and Gopal, 2008; Liu, Larson et al., 2011). Deploying bioenergy with carbon capture and sequestration (BECCS) results in a net reduction in atmospheric carbon. BECCS may be one of the few cost-effective carbon-negative opportunities available should anthropogenic climate change be worse than anticipated or emissions reductions in other sectors prove particularly difficult (Read and Lermit, 2005; Hansen, Sato et al., 2008). Previous work, primarily using Integrated Assessment Models (IAMs), has identified the critical role of BECCS in long-term (pre- or post-2100 timeframes) climate change mitigation, but has not investigated the role of BECCS in power systems in detail, or in aggressive timeframes (Milne and Field, 2013; Smith, Bustamante et al., 2014), even though commercial-scale facilities are starting to be deployed in the transportation sector (Gollakota and McDonald, 2012). Here, we explore the economic and deployment implications for BECCS in the electricity system of Western North America under aggressive (pre-2050) timeframes and carbon emissions limitations, with rich technology representation and physical constraints. We show that BECCS, combined with aggressive renewable deployment and fossil emission reductions, can enable a carbon-negative power system in Western North America by 2050 with up to 145% emissions reduction from 1990 levels. In most scenarios, the offsets produced by BECCS are found to be more valuable to the power system than the electricity it provides. Advanced biomass power generation employs similar system design to advanced coal technology, enabling a transition strategy to low-carbon energy.

An assessment of BECCS deployment as part of a suite of low-carbon technologies is a critical research need (Benson, 2014). Such an analysis requires detailed spatial and temporal assessment of distributed biomass supply, electricity demand, deployment of intermittent renewables, and electricity dispatch capabilities. We employ the SWITCH optimization model for long-term strategic planning of the electric system (Mileva, Nelson et al., 2013; Wei, Nelson et al., 2013). SWITCH leverages a unique combination of spatial and temporal detail to design realistic power systems that meet policy goals and carbon emission reduction targets at minimal cost (Nelson, Johnston et al., 2012). The version of the SWITCH model used here encompasses the region of the Western Electricity Coordinating Council (WECC), which includes the Western United States, two Canadian provinces, and a small portion of Mexico. WECC contains high quality wind and solar resources, but relatively limited bioenergy resources: the Eastern United States, for example, has a larger absolute resource (United States Department of Energy, 2011). Existing studies of low-carbon transitions in Western North America have generally reserved biomass for biofuels production, rather than for electricity (Long, John et al., 2011; Wei, Nelson et al., 2013).

Western North America contains biomass resources from forestry, wastes, agricultural residues, and dedicated energy crops, though supply is limited by land and sustainability practices (Fig. 4.B.1) (United States Department of Energy, 2011). In total, we identify 1.9×10^9 MMBtu (2000 PJ) of economically recoverable bioenergy available annually from solid biomass by the year 2030, sufficient for ~7-9% of modeled demand for electricity in 2050. Our estimates for availability in California are smaller than other studies, which tend to focus on 'technical potential' rather than 'economically recoverable' resources (Long, John et al., 2011; Williams, DeBenedictis et al., 2012). While barriers to biomass recovery exist even for economically recoverable resources, we choose these resources as a reasonable approximation of biomass potential. We model solid biomass fuel costs as a piecewise linear supply curve disaggregated for 50 regions across Western North America. Biomass supply from dedicated energy crops represents only 7% of the total supply, so direct land use impacts from the biomass feedstocks used in this study would be minimal. Dedicated feedstocks, such as switchgrass and pulpwood, tend to have higher prices than wastes and residues.

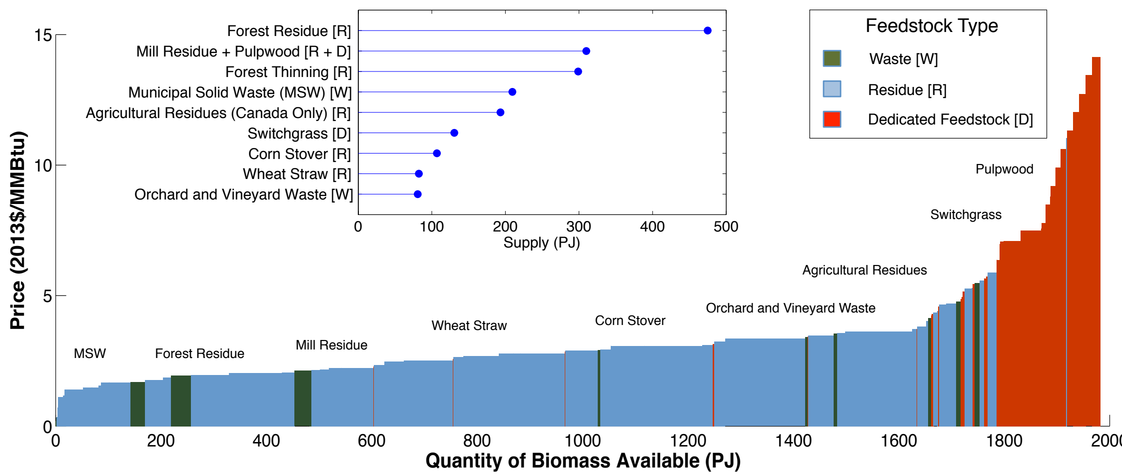


Figure 4.2.1 Supply curve of available solid biomass post-2030. Biomass can provide up to 2,000 PJ per yr of energy in 2030 for the electricity system, from a number of waste and dedicated sources. Labels on the supply curve represent the principal price region of a given biomass source. Feedstocks are classified as wastes (W), residues (R) or dedicated feedstocks (D). Dedicated feedstocks tend to be the most expensive.

The implications of BECCS for the economics and carbon emissions of regional power systems through 2050 have not been previously investigated in detail. To address this gap, we explore scenarios for the electricity sector that are consistent with economy-wide decarbonization, but vary the allocation of biomass across sectors of the economy. We explore scenarios with WECC-wide power sector CO2 emissions reductions from 1990 levels by 2050 ranging from 105% to 145%, which previous work has found would be consistent with economy-wide goals should biomass be used for electricity (Wei, Greenblatt et al., 2013). Our case without biopower mandates an 86% reduction in CO2 emissions from 1990 levels by 2050 (-86% No Biomass). We vary this scenario by disallowing CCS technologies (-86% No CCS No Biomass) and allowing biomass (-86%). To understand biomass deployment in carbon-neutral and carbon-negative power systems, we mandate a 105% reduction (-105%), 120% reduction (-120%), and 145% reduction (-145%) in CO2 emissions by 2050. These scenarios require aggressive R&D on CCS and BECCS over the coming decades. We continue operation of some existing nuclear plants, but do not allow new nuclear power. We do not conduct a complete economy-wide assessment of CO2 emissions across WECC or optimal biomass allocation among sectors.

Without biomass technologies (-86% No Biomass), the resource mix is reliant on other renewable energy technologies including wind, solar, hydro and geothermal for 86% of total electricity generated in 2050 (Fig. 4.2.2a). Low carbon power systems employ gas technologies (with and without CCS), storage, and transmission to compensate for renewable intermittency. Coal (with and without CCS) plays little to no role in energy generation because of its relatively high level of CO2 emissions (Fig. 4.2.2b). While CCS technology reduces CO2 emissions from coal, coal CCS still has higher emissions than gas CCS. Without CCS technologies (-86% No CCS No Biomass), the resource mix is even more reliant on renewable energy, up to 94% in 2050.

Biomass CCS technologies enable a power system more reliant on baseload and fossil technologies in 2050 at moderate power sector emission caps (between -86% and -105%). In the -86% case, coal CCS, biomass cofiring, and BECCS cumulatively provide 20% of electricity generated, enabling lower-cost gas resources to generate 22% of electricity while still meeting CO2 emission constraints. 43 GW of coal and biomass technologies are installed throughout western North America in 2050 (Fig. B5a). Due to the dispersed nature of the fuel resource, biomass deployment is distributed across the WECC. In the context of the electric power sector, if the cap on carbon emissions is held constant, the introduction of bioenergy for BECCS reduces power system costs, carbon abatement costs, and the need for electrical energy storage for intermittent renewable energy (Fig. B2a and Appendix B Text).

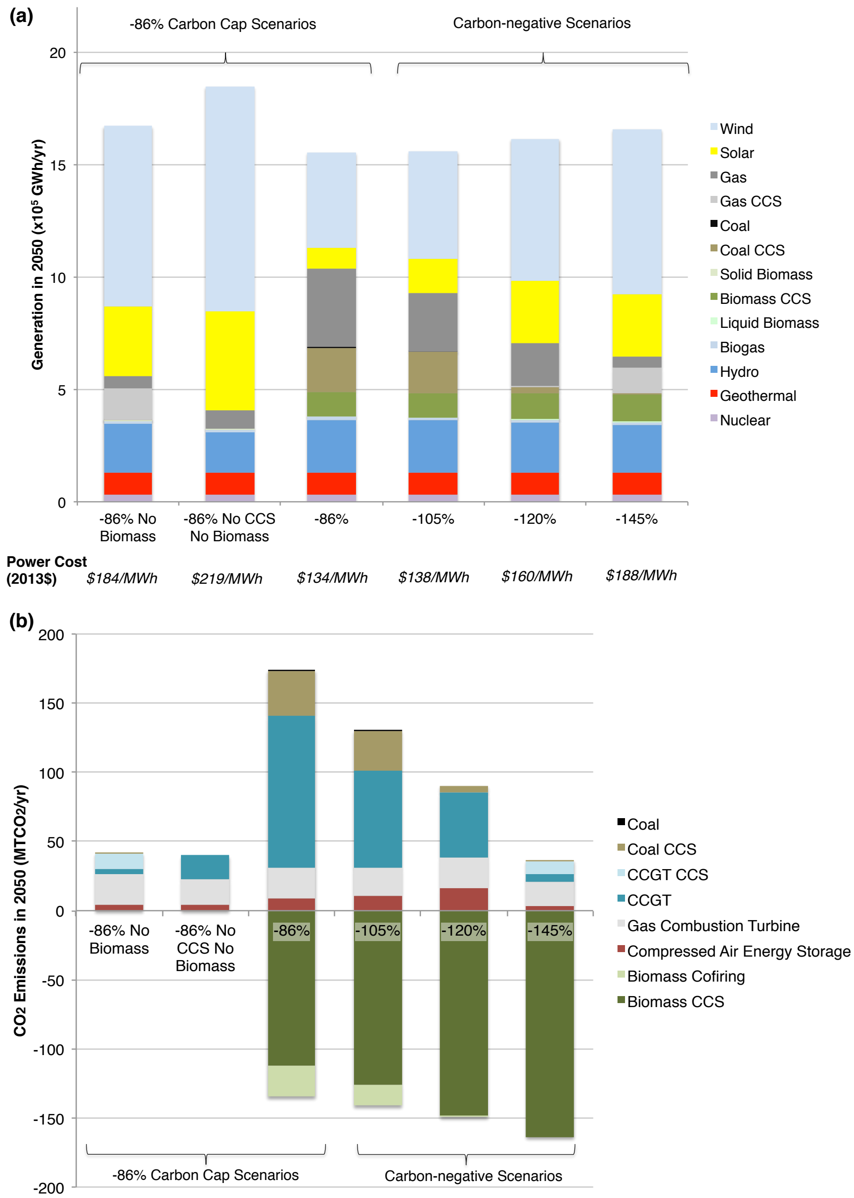


Figure 4.2.2 (a) Generation (10^5 GWh, gross), and cost of electricity (2013$/MWh) in 2050. Fossil fuel use is phased out as the power system becomes carbon-negative, transitioning from coal CCS and gas, to gas combined with CCS. 'Other' includes generation from coal, biogas, and bioliquid inputs. Total generation exceeds system load because of transmission, distribution, and storage losses as well as curtailment of generation on resources. **(b)** Yearly carbon emissions ($MtCO_2$/yr) in 2050. Biomass CCS and biomass cofiring CCS on coal CCS plants provide negative CO_2 emissions. As emissions limits are reduced, fossil CO_2 emissions shift from coal and CCGT to CCGT with CCS. BECCS can sequester ~165 $MtCO_2$/yr.

As the carbon cap becomes more stringent between the -105% and -145% case, we see CO2 emissions from combined-cycle gas turbine (CCGT) technology shrink before being captured via CCS, as well as increased renewable generation from wind and solar (Fig. 4.1.2). Coal CCS and biomass cofiring CCS play a significant role in the -105% case (~13% of average 2050 electricity generated), a smaller role in the -120% case (2%), and no role (0%) in the resource mix under the -145% case given the severity of the CO2 emissions constraint (Fig. B5b). Gas turbines are installed across all scenarios to provide flexibility, dispatchability, and system reserves.

Our -145% scenario demonstrates a power system that generates almost all electricity from renewable resources, representing how the power sector might be configured if climate change is severe, or emission reductions in non-electricity sectors are more expensive than the electricity sector. In our -145% case, biomass CCS plants provide carbon-negative baseload power in 2050, resulting in overall emissions of -135 MtCO2/yr in the WECC (Figs. 4.1.2). Generation, electricity costs, (Fig. 4.1.2a) and dispatch (Fig. 4.1.3 and Fig. B9) are similar between the -86% No Biomass and -145% cases, with the exception of BECCS technology deployment. Low-carbon scenarios without BECCS and carbon-negative scenarios with BECCS ultimately result in qualitatively similar deployment of gas and renewable generation.

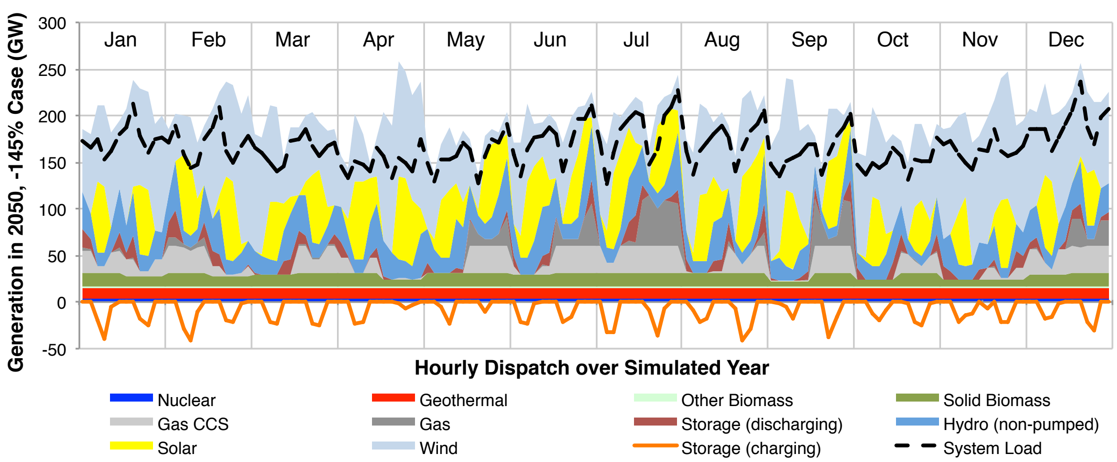


Figure 4.2.3 Hourly dispatch in 2050 in the -145% case. Power system dispatch is shown in sampled hours from two days (peak and median day) each month between January-December. With the exception of BECCS, dispatch is similar between the -86% No Biomass and -145% case (Fig. S9). Low-carbon scenarios without BECCS and carbon-negative scenarios with BECCS ultimately result in similar deployment of gas and renewable generation. "Other Biomass" includes both liquid and gaseous biomass supplies.

In all cases where biomass is allowed, the power system employs between 90-98% of all biomass supply available in 2050, regardless of the extent of CO2 reduction or availability of low-carbon flexible assets. This indicates that biomass systems are cost-effective in the context of low carbon power systems in Western North America, especially due to negative CO_2 emissions from BECCS. Given the very small amount of net CO_2 emitting infrastructure in the -145% case, we do not expect that that emissions could fall well below a 145% reduction with projected levels of biomass availability. While technology cost, lifecycle CO_2 emissions, and performance assumptions in carbon-negative power systems alter the relative deployment of coal CCS and intermittent renewables, they have little effect on biomass deployment.

We find that the value of BECCS lies primarily in the sequestration of carbon from biomass, rather than electricity production. This result reconfirms previous results found using IAMs (Klein, Luderer et al., 2014). To illustrate this point, we explore cases in which BECCS plants capture CO_2 emissions but do not produce electricity. The average cost of electricity when BECCS is used exclusively for carbon sequestration is only slightly higher (~6%) than when BECCS provides both sequestration and electricity (Fig. B6). Carbon sequestration from biomass, regardless of the technology employed or capital cost, could be a key driver of climate change mitigation pathways in the 2050 timeframe.

Our analysis has several implications for CO_2 reduction, technology development, and biomass allocation. Negative emissions from BECCS can offset CO_2 emissions from fossil energy across the economy. The amount of biomass resource available limits the level of fossil CO_2 emissions that can still satisfy carbon emissions caps. Efforts to expand biomass supply can increase demand for water, land, and fertilizer, or other ecosystem impacts (Abbasi and Abbasi, 2010; Solomon, 2010). Given the level of projected biomass availability in WECC, it would appear that there is little room for coal CCS technology to play a role in an energy system consistent with economy-wide emissions reductions goals. Gas CCS, however, can contribute moderately to economy-wide decarbonization due to its operational flexibility.

Our analysis suggests that installation of up to 10 GW of BECCS capacity between 2030 and 2040, with additional capacity additions thereafter, could be a key part of meeting stringent climate goals in the WECC. Such a goal would require a concentrated effort in finance, site selection, biomass sourcing, geological characterization, permitting, site-specific environmental impact assessments and community consultation. Biomass harvesting, drying, and transportation present logistical challenges to rapid deployment. However, we find necessary capacity deployment rates for BECCS to be smaller than that for other intermittent renewables or gas.

Advanced biomass power generation technology employs similar system design to advanced coal technology, including CCS and integrated gasification combined cycle (IGCC) systems (Corti and Lombardi, 2004). Such systems boast higher efficiency and more easily capture CO_2 emissions than conventional steam turbines; these characteristics become even more desirable in light of biomass' lower energy density, higher feedstock cost, and distributed geographic nature. Research needs include systems integration and technology advancement in gasification, air separation, gas cleaning, shift catalysis, and gas turbines that operate on H_2-rich syngas (Farrell and Gopal, 2008;

Maxson, Holt et al., 2011)2 21. Moving forward, the fossil fuel industry could embrace higher and more efficient levels of biomass utilization combined with CCS technology development as a transition strategy to low-carbon energy. BECCS could enable some of the world's largest carbon emitting entities to instead become some of the world's largest carbon sequestering entities.

Biomass could enable CO2 reduction not only in the electricity sector, but also the transportation and industrial sectors for fuels, heat, and chemicals. We estimate that cellulosic biofuel production from available biomass in WECC can reduce emissions by 75 MtCO2/yr by displacing gasoline, based on literature conversion efficiency and near-term carbon intensity values (Farrell, Plevin et al., 2006). In contrast, if biomass is made available to the power sector, BECCS can sequester 165 MtCO2/yr and also displace fossil electricity. At the conversion efficiencies assumed in this study, bioelectricity contains 28-45% of the net energy of candidate cellulosic ethanol conversion pathways, but can provide as much as 41% more transportation miles because of the high efficiency of battery electric drive vehicles (Farrell, Plevin et al., 2006; Campbell, Lobell et al., 2009).

Our analysis indicates that while valuable to the power sector, carbon sequestration from biomass may be more cost-effective in other sectors. We find BECCS technology deployment at abatement costs as low as $74/tCO2 in the -86% case, with more stringent emission caps incurring higher abatement costs. Such costs are slightly higher than afforestation schemes (~$5 – 40/tCO2), biochar projects in North America ($30 – 40/tCO2), and cellulosic biofuel production ($35/tCO2), but are far lower than projected abatement costs for direct air capture of CO2, which has been assessed as high as $1000/tCO2 (Intergovernmental Panel on Climate Change. Working Group 3, 2007; Lutsey and Sperling, 2009; Pratt and Moran, 2010; House, Baclig et al., 2011). Should carbon sequestration be more effective via alternative abatement methods, the electric power sector would find it economical to purchase those offsets. A roadmap of economy-wide biomass policy focused on CO2 reduction should account for both the technical potential and economic costs of biomass deployment across sectors. Increasing efficiency, reducing costs, and commercializing carbon-negative biomass technologies could make such a roadmap possible.

Materials and Methods

Biomass Technologies. SWITCH inputs include technology cost profiles, construction timeframes, outage rates, generation flexibility, retrofit ability, heat rate, and cycling penalties for a broad range of existing and new conventional and renewable energy generation technologies. Technical performance metrics and evolution of capital and operations and maintenance costs are drawn primarily from Black and Veatch (Black & Veatch, 2012). We assume that future biomass plants will use IGCC technology, while existing plants use steam turbines. CCS technologies are modeled with a default capture efficiency of 85%, and are available for installation on biomass IGCC, coal, and natural gas technologies after 2025. We do not explicitly model criteria pollutants, which may require additional control technology to be installed on coal and biopower technologies.

While Black and Veatch estimates capital and operating costs for biomass IGCC plants, their dataset does not include similar values for BECCS plants. As assumptions between cost datasets can differ substantially, we choose to estimate cost and efficiency parameters for BECCS plants from other similar plant types. We derive the capital cost of CCS equipment, the efficiency penalty of performing CCS, and increase in non-fuel variable operations and maintenance costs for BECCS from coal IGCC and coal IGCC CCS systems. Our BECCS capital cost estimates are within 5% of those by the National Energy Technology Laboratory (NETL) for biomass IGCC-CCS facilities (Matuszewski, Black et al., 2012). Increasing the capital cost of BECCS would likely not lower deployment due to the high value of carbon sequestration. As a large amount of the biomass resource is already deployed in our scenarios, lowering the capital cost would also be unlikely to affect deployment.

Biomass Supply. Fuel costs for solid biomass are input into the SWITCH model as a piecewise linear supply curve for each load area. This piecewise linear supply curve is adjusted to include producer surplus from the solid biomass cost supply curve in order to represent market equilibrium of biomass prices in the electric power sector. As no single data source is exhaustive in the types of biomass considered, solid biomass feedstock recovery costs and corresponding energy availability at each cost level originate from a variety of sources. We consider two scenarios for biomass life-cycle assessment (LCA): 1) carbon-neutrality, as feedstocks are primarily wastes or low-input crops grown on marginal lands, and 2) a sensitivity scenario with solid biomass penalized at 10% of its biogenic carbon content. In the carbon-neutral cases, we assume that direct emissions from harvesting and transport—a small source of emissions—will be minimized as the entire economy is decarbonized (Rhodes and Keith, 2005). The sensitivity case represents increased emissions such as those from transportation, fertilizer, or soil organic carbon (SOC) from residue collection, which recent empirical work suggests may be larger than previously thought (Liska, Yang et al., 2014).

Biomass Cofiring and Modeled Scenarios. Cofiring is allowed up to 15% of total output from a single coal plant. When cofiring is installed on a plant with CCS technology, we assume that the heat rate increases by the same percentage when sequestering carbon as does coal IGCC relative to coal IGCC CCS.

CCS Reservoirs and Transportation. Large-scale deployment of CCS pipelines would require pipeline networks from CO_2 sources to CO_2 sinks. We require CCS generators that are not near a CO_2 sink to build longer pipelines, thereby incurring extra capital cost. If a load area does not does not contain an adequate CO_2 sink within its boundaries, a pipeline between the largest substation in that load area and the nearest CO_2 sink is built. We derive pipeline costs from existing literature. CCS plants must send all of their CO_2 output to their closest reservoir.

Scenario Development. All scenarios enforce a carbon cap and existing Renewable Portfolio Standard (RPS) laws. We disallow new nuclear generation. Electricity demand profiles include extensive energy efficiency, electric heating, and electric vehicle penetration consistent with economy-wide decarbonization. We sample hourly demand for each of 50 areas within WECC for six hours of each of 12 representative days in the decades 2020–2050. Investment decisions are made in four periods between 2016-2055; these periods are 2016-2025 ("2020"), 2026-2035 ("2030"), 2036-2045 ("2040") and 2046-2055 ("2050"). In each modeled hour, demand must be met by the optimization, as well as capacity and operational reserve margin constraints to ensure system reliability.

5 Natural Gas leakage increases electricity costs and reduces consumption under carbon caps

We started working on Switch-WECC in the early days of the Natural Gas boom prompted by hydraulic fracturing. The low prices of NG, high efficiency of Combined Cycle Gas Turbines, and low emissions relative to led to coal pointed to a mitigation pathway of replacing coal with natural gas in the next few decades. Over time, data emerged describing potentially high methane leakage rates in the natural gas supply chain, which threw the earlier result into question. In this chapter, I led an investigation into how methane emissions in the Natural Gas supply chain impacts roles natural gas (NG) can play in a low emission power grid. We found that leakage rates significantly reduce the use of NG as a direct substitute for coal, but have a smaller impact on the use of combustion turbines for reserves and peaking capacity. These results indicate that current industry and policy trends of seeking emission reductions through large amounts of new natural gas are useful in the near-to-mid term, but have a clear expiration date that will be hastened if we continue methane emissions. This chapter is being prepared for journal submission in collaboration with Ana Mileva, Jimmy Nelson, Jalel Sager, Matthias Fripp, and Daniel Kammen.

A growing body of literature indicates that official methane emissions or “leakage” values underestimate true rates in the Natural Gas (NG) supply chain. Several publications have assessed leakage impacts on greenhouse gas emissions of individual generators, but none have examined impacts on a larger portfolio that uses NG to complement renewables. This study uses a power system investment optimization model, SWITCH, to examine the roles of NG in a low-carbon grid and the impacts of leakage in Western North America. Here we show that leakage rates significantly reduce NG as a direct substitute for coal, but has a smaller impact on the use of combustion turbines for reserves and peaking capacity. Higher leakage rates increase electricity costs in the optimal solutions by an average of 1.3% ±0.068 and decrease NG consumption by 18% ±0.55 for each percentage point increase in the leakage rate in the next decade. Increased leakage can increase the role NG plays to complement renewables during 2020-2030 under moderate emission caps by reducing its capacity factors as well as increasing the deployment of NG Combustion Turbines with Compressed Air Energy Storage in 2030 provided that alternate technologies such as low cost batteries do not outcompete it. In the 2040 and 2050 timeframes with tighter emission caps, NG is already used primarily to complement renewables and higher leakage rates tend to decrease its use in any role.

5.1 Introduction

Reducing greenhouse gas emissions from the electricity sector is critical to mitigate climate change and secure sustainable future. Many national plans consider Natural Gas (NG) a bridge fuel for electricity decarbonization because new efficient NG plants have half the carbon intensity of old coal plants, NG gas costs are competitive with coal due to hydraulic fracturing, and NG ramping capabilities can compensate for renewable variability. Broadly speaking, NG can play two distinct roles for decarbonization. The first role is to directly replace old "baseload" coal plants with new efficient NG Combined Cycle Gas Turbines (CCGT) and operate the new plants in "baseload" mode. The second role is run a diverse fleet of NG generators as needed to compensate for the variability of renewable wind and solar power.

The majority of "bridge fuel" discussions have focused on using NG to replace coal for baseload power. This prompted some controversy and concern that building a NG plant implies a commitment to run it constantly at full capacity for its operational life, which is incompatible with long-term emission reduction targets. Most international discussions agree that industrialized nations need to reduce greenhouse gas emissions to at least 80% below 1990 levels by 2050 to have a reasonable chance at avoiding the most catastrophic risks of global warming (Intergovernmental Panel on Climate Change. Working Group 3, 2007). If the entire emission budget for WECC (the electricity grid for the western portion of North America) was allocated to high-efficiency NG plants, they could supply about 96% of 2020 demand, but only 8% of 2050 demand. This represents a 91% reduction of the amount of NG consumed in 2013 by the electricity sector. Clearly, the first role of NG as baseload has an expiration date, but there is no technical reason why NG infrastructure cannot transition into the second role of complementing renewables on an hourly or seasonal basis. Some people may have economic concerns about recovering costs if energy sales drop, concerns which could be addressed by capacity markets that pay for the option of purchasing energy as needed and ensure a cash flow that can cover fixed costs.

The overall Greenhouse Gas (GHG) intensity of NG electricity is highly dependent on methane emissions, or "leakage" in the fuel supply chain. Methane (the principal component of NG) is a greenhouse gas that is 86 and 34 times more potent than CO_2 in 20- and 100-year timeframes (Stocker, Dahe et al., 2013). Leakage is extremely diverse in its sources and magnitudes, and less than one percent of equipment can be responsible for the majority of facilities and pipelines leaks (National Gas Machinery Laboratory, Clearstone Engineering et al., 2006). Large intentional venting have been routine in the past to clean liquid or debris from wells, but those are expected to decline in the US due to recent EPA regulations (EPA, 2012; EPA, 2014b). National average leakage rates are not known with precision and is the subject of active research efforts. Bottom-up studies that directly measure equipment in the supply chain poorly estimate leakage because emission rates can vary significantly over time, and voluntary study participation often results in a sampling bias where companies only allow access their best performing facilities. Top-down studies that measure overall atmospheric methane levels have various difficulties in measuring precise levels of the trace gas over a large area, differentiating fossil methane from biogenic methane, and isolating the portion of fossil methane that originates upstream of electricity generators. Methane emissions that occur in residential NG distribution systems, coal mining, or oil fields are bad for global warming, but are largely tangential to the bridge fuel debate. A recent review paper found that official methane emission inventories systematically underestimate actual leakage rates across scales (Brandt, Heath et al., 2014) (Fig 5.1).

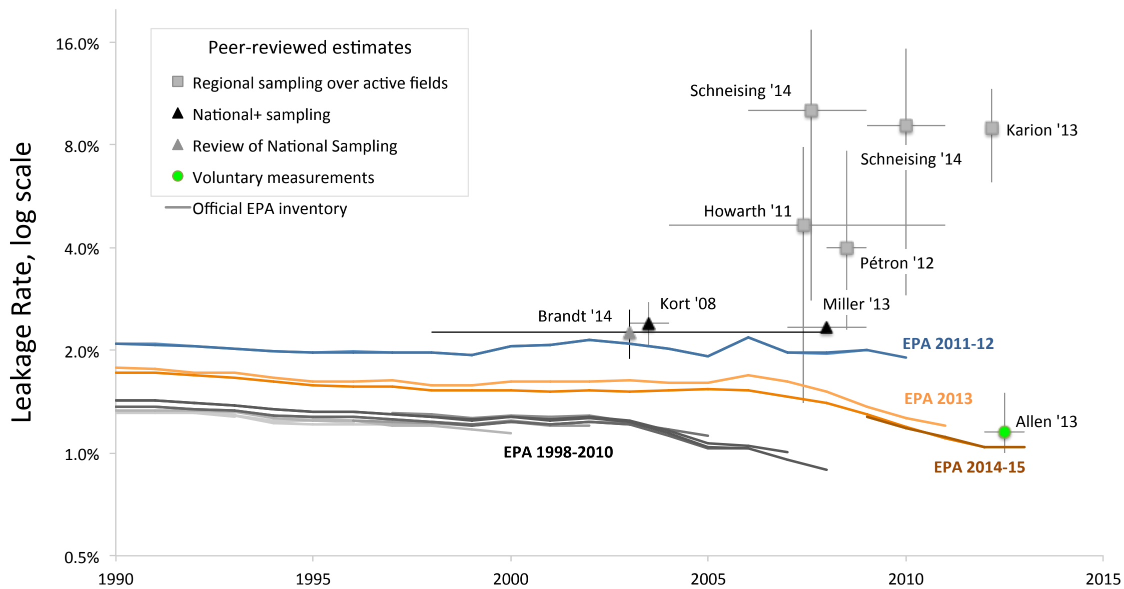


Figure 5.1 Leakage estimates for Natural Gas supplies to the electricity sector from current EPA Greenhouse Gas Emission Inventories are 1.5 to 8.6 times smaller than non-voluntary third-party measurements. 17 years of EPA inventories are depicted with lines. Third-party studies are depicted as points with their time span as a horizontal bar and their reported range of possible values as a vertical bar on a log scale. The point's style indicates the type of research methods used to estimate leakage rates.

EPA national inventories of historical methane emissions have undergone three major revisions since their inception in 1998, but consistently fall below measurements published in peer-reviewed journals. EPA inventories mostly rely on a dated 1996 report jointly written by an industry group and the EPA, plus data streams of industry statistics and self-reports (EPA, 2015). In 2011, the EPA retroactively increased inventories based on engineering estimates of removing liquids and debris from wells during normal operations and hydraulic fracturing. New regulations in late 2012 prompted a rapid industry response in the form of a report and stakeholder input which led to the EPA lowering inventory estimates in 2013 (EPA, 2013b). Meanwhile, Kort and Miller rigorously documented higher leakage levels across North America (Kort, Eluszkiewicz et al., 2008; Miller, Wofsy et al., 2013). Numerous other authors documented logarithmically higher leakage in high-growth NG fields using less geographically representative datasets (Howarth, Santoro et al., 2011; Pétron, Frost et al., 2012; Karion, Sweeney et al., 2013; Schneising, Burrows et al., 2014). The lowest documented levels were based on detailed voluntary equipment-level measurements and show what is technically achievable (Allen, Torres et al., 2013), although a recent paper raised concerns that sensor malfunctions may have underreported leakage rates in that study (Howard, 2015).

Current EPA estimates do not reflect expected emission increases from historical events of less-regulated regional hydraulic fracturing activities, nor do they adequately represent reporting bias from small facilities being excluded or fallacious reporting. In the 2013 national greenhouse gas emission inventory, the EPA expressed an awareness of emissions inventory being lower than recent studies and requested feedback for integrating scientific findings (EPA, 2013a). However, the 2014 inventory failed to integrate peer-reviewed datasets and instead reduced methane emissions inventories by an additional 10%. Ironically, this report cited five studies documenting a need for increasing estimates of methane emissions and summarized many suggestions from commenters for incorporating that research (EPA, 2014a). The 2015 inventory did not significantly revise methane emissions estimations and failed to integrate peer-reviewed datasets or follow up on suggestions received in 2014 (EPA, 2015). This prolonged and systematic bias that favors industry self-reporting to scientific peer-reviewed observations and comments is troubling, particularly since it directly opposes their stated intents. Overall, the gap between voluntary measurements and third-party measurements suggests a need for more pervasive monitoring or random inspections to identify high-emitting equipment and facilities.

5.2 Results

To assess the impacts of leakage on the roles of Natural Gas in an integrated portfolio that includes large amounts of renewable power, we ran a series of scenarios within the SWITCH-WECC model. SWITCH is a grid investment optimization model that includes a simplified formulation of dispatch operations in order to endogenously account for renewable integration requirements (Fripp, 2012; Nelson, Johnston et al., 2012; Mileva, Nelson et al., 2013). The objective function of SWITCH minimizes the levelized cost of providing electricity subject to reliability constraints and policy goals. SWITCH identifies least-cost portfolios that are optimal points on the efficiency frontier of technical feasibility. The results from SWITCH do not predict what portfolio will actually be built, but indicate what is technically achievable. SWITCH-WECC includes a detailed representation of existing generators, storage facilities and transmission lines in the Western Electricity Coordinating Council that roughly spans the western portion of North America. This model does not include NG wells, processing facilities, pipelines or storage sites. This geographical region provides a useful lens into this issue because the United States is the largest global consumer of NG, and has recently been setting policy goals to reduce leakage as well as overall greenhouse gas emissions.

Given the inherent uncertainty about actual leakage rates, we performed a sensitivity analysis to assess impacts at leakage rates ranging from 0 to 8%. We chose to use a 20-year Global Warming Potential of 86 for methane as a simple linear proxy for the complex and non-linear time dynamics of global warming and the potential for near-term emissions to trigger climactic “tipping points”. In all of our scenarios, we treated leakage rate as an exogenous factor that remained constant over time and imposed an indirect emissions penalty for the consumption of gas by the electricity sector (see Methods). That is, methane emissions scale linearly with total consumption in each decadal investment period in this study. In reality, emissions will depend on how much infrastructure is installed and pressurized, how much it is used, and how much effort is applied to minimizing leaks. We based emissions on aggregate long-term consumption because it is a proxy for both how much infrastructure is installed to support the electricity sector and how much it is used. We did not model how the NG sector could reduce leakage because we lack accurate data on current methane emissions and the emission abatement supply curve. Consequently, these results should not be interpreted as a simulation of two-way interactions between the natural gas and electricity sectors. These results can be interpreted as quantitative estimates of the value of reducing leakage and how various levels of leakage could impact deployment and use of generation technologies in optimized portfolios.

The base scenario conservatively assumes little technological advancements will be available to deploy at scale over the next 40 years. This prohibits new Nuclear as well as Carbon Capture and Sequestration (CCS) technologies, but allows Sodium-Sulfur Batteries as well as Compressed Air Energy Storage which adds a storage component to NG combustion turbines (Gas CT + storage, or CAES). The base scenario operated under a carbon cap of 86% below 1990 levels by 2050 based on the presumption that the electricity sector may be called on to decarbonize more extensively than the rest of the economy.

Other scenarios adjusted one or more assumptions from the base scenario. Two low-emission baseload scenarios allowed CCS, with or without Nuclear. Three green technology scenarios dramatically reduced the cost of solar, storage, or solar & storage. and storage, individually and together. Four carbon cap sensitivity scenarios evaluated 2050 targets of 35, 70, 90 and 95% below 1990 levels. The 35% Carbon Cap scenario represented the 2030 emission goals of the Clean Air Act Section 111, also known as the Clean Power Plan (EPA, 2014c). One extreme climate impact scenario reduced the availability of water for Hydropower electricity by 50% in all seasons and future periods. Overall, these 11 scenarios required 99 distinct runs that took roughly 15,000 cpu-hours to complete on a high performance computing cluster. We chose these scenarios to explore overall tradeoffs and interactions. Including additional scenarios and permutations would have improved the rigor of this study, but we were limited by time and computing resource.

Increased rates of leakage caused increases in the cost of supplying electricity while meeting a carbon cap (Fig 5.2) by placing greater pressure on emissions budgets (Fig 5.3), causing the system to install more expensive alternatives (Fig 5.4). The cost impacts were relatively consistent across scenarios in 2020, after which they increased in magnitude and diverged across scenarios. Increased rates of leakage caused overall decreases in NG consumption by the electricity sector. The impacts were generally consistent across scenarios and tended to decrease in 2040 and 2050 as tight carbon caps limit NG consumption regardless of leakage. Paradoxically, NG consumption increases slightly in 2020 between 0 and 1% leakage rate. This can be interpreted as methane emissions putting pressure on the carbon budget and the cheapest way of relieving that pressure is to substitute Coal baseload capacity with Gas CCGT plants, plus some renewables. This situation is found in all scenarios except the Cheap Solar and Cheap Solar & Storage scenarios which increase Solar instead of replacing Coal with Gas.

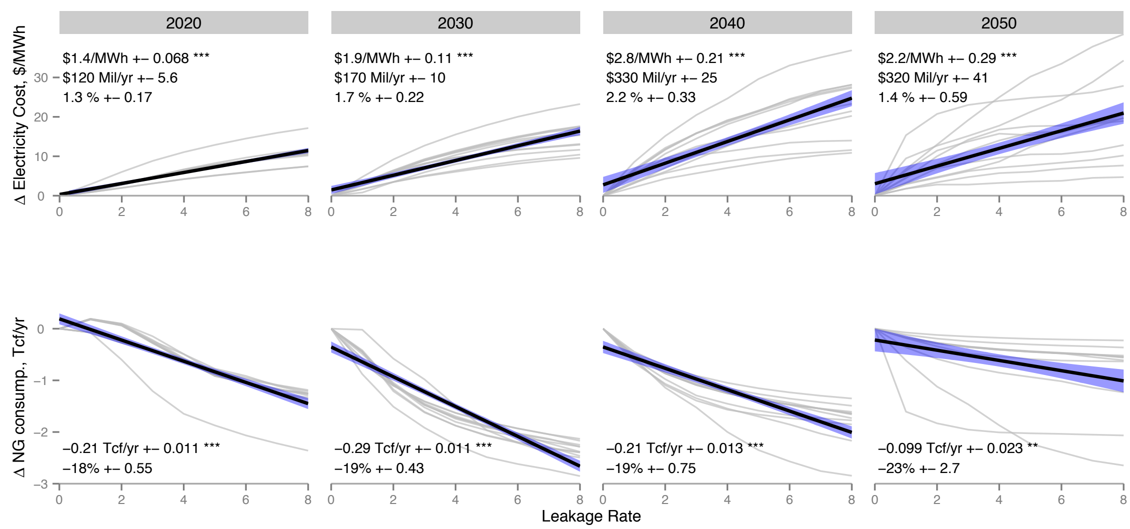


Figure 5.2 Changes in electricity cost and Natural Gas consumption in response to leakage. Each grey line depicts the change in output of each scenario relative to no leakage in that scenario. The black line and blue confidence interval depict the average changes across scenarios and leakage rates. Numerical values provide average impact per percentage point increase in leakage rate; these are also given in units of system costs and percentage change in the response variable for added context. ** $p<10^{-3}$ *** $p<10^{-5}$

Overall, the more dependence a system has on natural gas, the larger response it has to leakage rates. Leakage rates have the large cost impacts in the Reduced Hydro scenario in 2020-2040 because that system relies more heavily on flexible CCGT capacity to replace Hydropower. In 2050, Reduced Hydro's cost impacts fall to the middle of the pack, possibly because it was already forced to make infrastructure investments compatible with very low emissions. The availability of alternatives to gas also plays a role in mitigating cost impacts. The cheap solar scenarios (with or without cheap storage) have the lowest cost responsiveness to leakage rate in 2020-2030 when system flexibility is not a major driver of cost, and the Cheap Solar and Storage scenario has some of the lowest cost responsiveness in 2040-2050 when low-emission flexibility becomes a major driver. See supplemental text for more discussion of drivers of 2040 and 2050 cost responses.

Leakage also has a striking impact on the emission budget. As leakage rates increase from 0, methane emissions rapidly take over the carbon budget (Fig 5.3). The fact that methane emissions can account for the majority of the emissions budget under high leakage rate scenarios in 2030 and beyond indicates that NG is valuable to the electrical system, especially as emission cap decline and the shares of intermittent renewable power increases. These trends are consistent across scenarios (Fig A2), with the exception of scenarios that allow CCS where Coal CCS tends to dominate the carbon budget at leakage rates of 3% or above in 2050. It is worth noting that extremely high leakage rates are inconsistent with carbon caps in 2040 or 2050 because the cost of emission permits would strongly incentivize methane emission reductions in that timeframe.

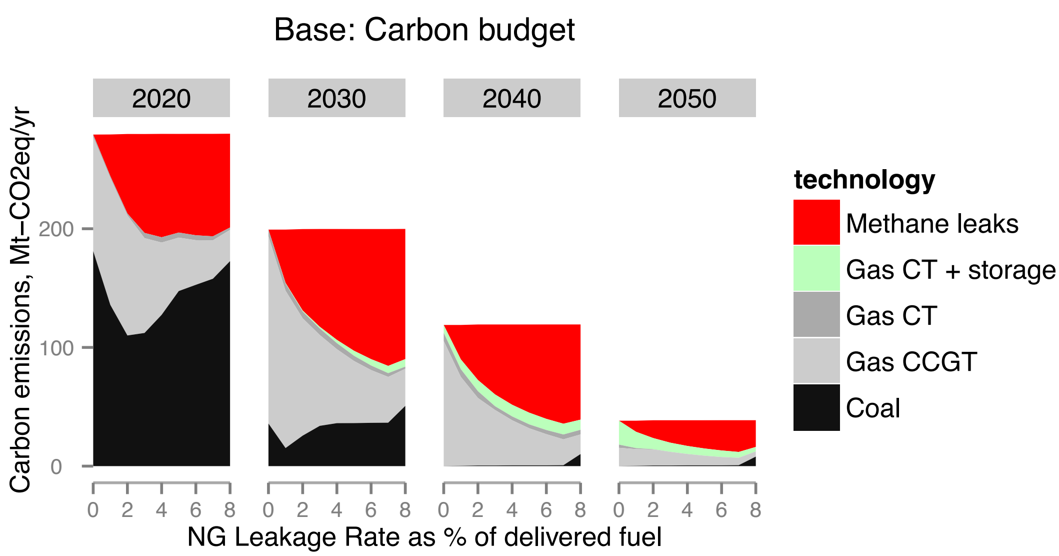


Figure 5.3 Carbon budget allocations for the base scenario based on least-cost portfolios. Methane rapidly displaces CO_2 emissions in the carbon budget under non-zero leakage rates, occupying the majority of the carbon budget under high leakage scenarios in 2030 and beyond. Coal is the single largest emitter in 2020, but is mostly retired as the carbon budget tightens over time. Coal can displace natural gas Combined Cycle Gas Turbines in the carbon budget if leakage increases beyond thresholds values in any time frame. NG Combustion Turbines (CTs) are never allocated significant portions of the carbon budget. Under a tight carbon cap in 2050, the value of NG is stretched by augmenting CTs with Compressed Air Energy Storage to balance renewable energy on a daily basis.

The overall impact of leakage on portfolio composition is to decrease NG CCGT and CT capacity while increasing installations of other generation technologies, especially renewables. The average portfolio response is relatively consistent between scenarios in 2020 and shows greater variation in later periods (Fig 5.4, left). In the 2020 and 2030, an average of 41 and 59% of CCGT capacity is dispatched as baseload power at a leakage rate of 0, but the role of NG as baseload is highly sensitive to leakage rate and essentially disappears when leakage rates exceed 4%, the point at which the carbon intensity of CCGT exceeds that of Coal (Fig A1). Gas CT capacity decreases with leakage in 2020, but its power output shows little response. Overall, the role of CTs as peaking capacity with low capacity factors remains constant across time periods, leakage rates and scenarios. Although the overall portfolio varies between scenarios, the impact of leakage on the roles of natural gas were extremely robust. The notable exception is that cheap battery storage could replace NG-CAES storage in later periods.

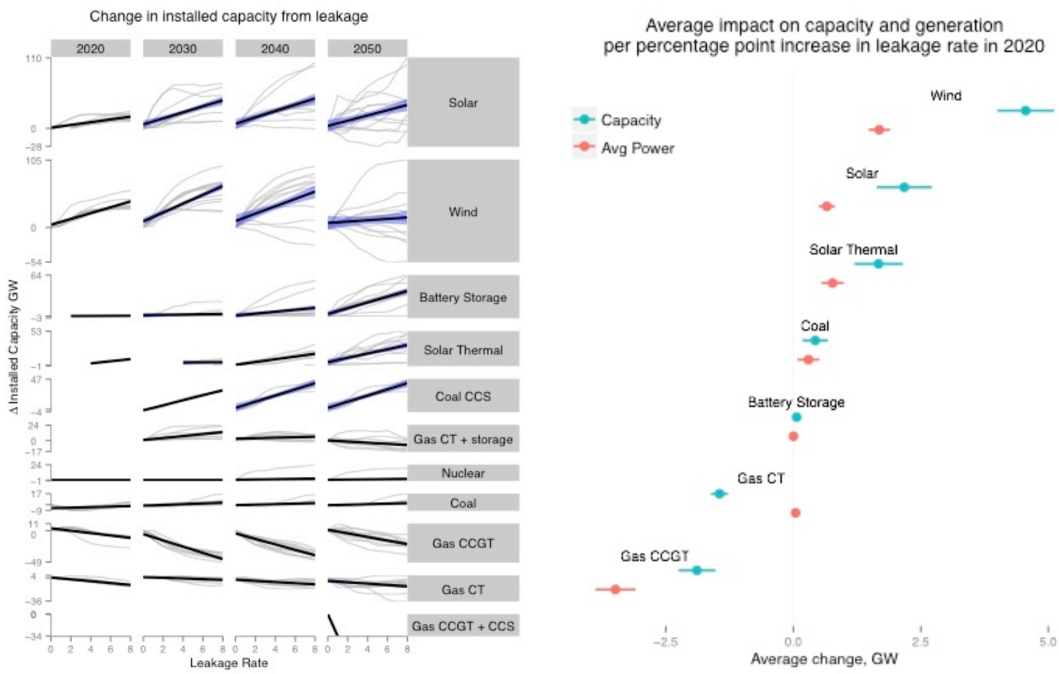


Figure 5.4 *Left* Impacts of leakage on portfolio composition is shown as a grey line for each scenario. Technologies are ordered by maximum change in capacity in any scenario or period. Average impacts across scenarios and leakage rates are shown as black trend lines with blue confidence intervals. New CCS technologies and Nuclear are only installed in the two scenarios where they are allowed. The Nuclear trend line appears flat because all scenarios have legacy Nuclear plants that stay online regardless of leakage rate. Technologies with a maximum response of less than 15 MW are excluded for clarity (Geothermal, Hydropower, Biomass, and Distributed Solar). *Right* Average impacts of leakage on installed capacity and average power output in 2020 across all scenarios and leakage rates. Technologies ordered by average capacity impacts in 2020. Blue points depict change in GW capacity per percentage point increase in leakage for each technology in 2020, averaged across scenarios with lines indicating 95% confidence intervals. Red points depict change in GW average power output per percentage point increase in leakage rate. For wind and solar projects, capacity increases faster than power due to their dependence on weather. For Combined Cycle Gas Turbines (Gas CCGT), leakage impacts average power dispatched more than average capacity installed.

The portfolio changes in 2020 are non-linear between 0 and 2%, but roughly stabilize at 3% and higher leakage rates. As leakage increases from 0 to 1% and stresses the carbon budget, the system responds by directly replacing Coal baseload electricity with CCGT while adding Wind. As leakage rates climbs to 2%, additional coal is retired, more Wind is installed and CCGT shifts to complement it by adding capacity and reducing its capacity factors. At leakage rates of 3% or higher, Coal baseload comes back along with a small amount of Geothermal (subject to resource constraints). More wind and solar are added, and CCGT increasingly shifts to complement them with lower capacity factors and reduced capacity (Fig 5.4, right).

As carbon caps become tighter in 2030 and beyond, the system increasingly looks to Compressed Air Energy Storage (CAES or Gas CT + Storage) for energy balancing and within-day arbitrage. In a standard gas combustion turbine, roughly 75 percent of the gross electricity output operates a pump to pressurize the fuel-air mixture for the turbine. In a CAES system, an air pump uses grid energy to store high-pressure air in either underground formations or aboveground tanks, which is later used by a gas turbine. This enables the turbine to increase its net power output by roughly a factor of 4 at the cost of storage energy losses. In theory this technology could be applied to more efficient CCGTs as well, and could even be retrofitted to existing plants. It is worth noting that CCGT capacity could likely have a longer useful life and higher capacity factors in these scenarios – regardless of upstream emission rates - by incorporating CAES. This analysis only considers CAES with CTs because it has demonstration projects and is the only version of the technology under active discussion. The version of CAES modeled here can move energy between different hours in a single day, but not from day to day.

On average, higher leakage rates increase the installed capacity of CAES in the 2030-2040 timeframes when CAES and increased renewables displace energy from CCGT. Under the tighter carbon cap of the 2050 timeframe, methane leakage causes CAES capacity to be replaced by lower-emission battery storage. On average, increased leakage prompts an increase in CAES dispatch in 2030 and a decrease in 2040-2050. The dispatch of CAES is less responsive to leakage rate than CCGT in all timeframes because of it has superior ability to complement variations of renewable power over the course of a day.

The responses of Solar [PV] and Wind capacity vary significantly by scenario and leakage rate in 2040 and 2050, with installed capacity decreasing in response to leakage rate for some scenarios. In many scenarios (including the base case), increasing leakage rates in 2050 initially prompt Solar capacity to be replaced by Solar Thermal capacity with 6 hour energy storage that can be dispatched at night and have less intermittency from passing clouds. The ability of a system to incorporate large amounts of Solar Photovoltaics is dependent on ramping abilities of dispatchable generators such as NG. This trend is most pronounced for the Reduced Hydro scenario, which has more limited flexibility to complement Solar. Solar capacity also tends to fall if low emission baseload technologies such as Coal CCS or Nuclear are available because those systems have overall less flexibility. In contrast, scenarios with low-cost battery storage dramatically increase solar capacity as leakage rates increase while simultaneously reducing wind capacity which has stronger seasonal variation.

Certain technologies show little response to leakage for various reasons. Higher leakage rates prompt earlier installation of Geothermal and Biomass capacity, but these responses are limited impact on the overall system due to relatively small potential capacity in these scenarios. If more geothermal sites are mapped, or if more Biomass is allocated to the electricity sector, the system would likely respond in similar ways as other low-carbon baseload options. Distributed Solar is not installed beyond policy requirements in these least-cost portfolios because Central Solar with tracking has lower costs and higher capacity factors. Should those cost dynamics change or other incentives be modeled, Distributed Solar would likely have similar response dynamics as Central Solar. Hydropower has no new potential capacity available so shows little response to leakage.

Many portfolios developed by these scenarios were susceptible to modest amounts of excess emissions in 2040-2050 when system dispatch was simulated on a complete year of hourly data per period. These emission overruns were caused by overfitting to the sampled timepoints used to optimize each portfolio which led to overestimating renewable energy production. In these situations, spare natural gas capacity was dispatched more heavily to compensate, which meant that emission overruns increased with higher leakage rates. This illustrates that methane leakage limits the role of Natural Gas generators for capacity reserves because its dispatch will be limited by an emissions cap. If high leakage rates persist, we may need to look for lower emission alternatives for capacity reserves. For these scenarios, the excess emissions from high leakage rates is not a major concern because economic pressures in a future with emission regulations would incentivize adoption of leakage-reducing equipment and operating procedures.

5.3 Discussion

This study was performed on the western portion of North America that has abundant high-potential solar and wind resources than can substitute for natural gas. Cost impacts of leakage in other regions of the world would also depend on substitution options. For example, cost impacts would likely be higher in the Eastern portion of North America due to less abundant solar and wind resources. Russia, the second-largest consumer of NG, may see smaller cost impacts than Japan due to large differences in undeveloped renewable energy potential and hydropower available for balancing. Emission policies and appropriate accounting of leakage would also play a large role in cost impacts. In the United States in the early days of the hydraulic fracturing boom, leakage rates appeared to increase through use of sloppy practices, though this is not comprehensively documented. Currently, the US NG industry is still expanding but is making greater efforts to reduce leakage, largely in response to public and regulatory pressure. In a cost-effective future under emission caps, the US NG industry will need to reduce both leakage rate and production levels. If other countries expand their use of NG as part of a larger emission reduction plan, they would benefit from training their NG industry in best practices and enacting regulation and monitoring programs to minimize leakage.

Compressed Air Energy Storage has the highest growth potential of any NG technology examined, and CAES potential would likely grow if applied to combined cycle plants. Adding Carbon Capture and Sequestration (CCS) with post-combustion amine capture does not look promising and could be counter-productive under high leakage rates because energy demands of amine capture would require more fuel consumption and large upstream emissions. The alternative CCS technology of oxygen combustion that could provide near 100% capture rates and demand response during oxygen production could extend the role of NG if leakage rates are low, capital costs and energy requirements are reasonable, and carbon sequestration is proven to be stable and low-risk.

In this study, we modeled methane emissions attributable to the electricity sector based on the consumption of NG by the electricity sector. An alternative approach would be to scale emissions linearly with the infrastructure capacity of the NG sector: number of wells and processing facilities, miles of pressurized pipeline, etc. If we had taken the latter approach, then the optimization would tend to decrease infrastructure capacity while increasing its utilization and installing more NG storage near generators to decouple peak consumption from peak pipeline flow. If NG storage were unavailable, the optimization would likely reduce peak consumption and/or NG generation capacity in efforts to reduce methane emissions.

Leakage will dominate a dwindling carbon budget to the extent it persists, but leakage rates are being reduced. In 2012, the EPA began mandating gradual installation of cost effective leakage control equipment and more stringent reporting requirements for NG (EPA, 2014b). These measures are expected to decrease leakage, especially during completion of hydraulically fractured wells, but these improvements have not yet been documented in peer-reviewed literature. To permanently reduce leakage, we need more comprehensive monitoring programs and improved accounting practices to rectify observations with emission inventories. Comprehensive monitoring can alleviate concerns about sampling bias underestimating leakage rates and ensure that the small number of equipment malfunctions that dominate supply chain leakage are identified. We can expect more room in the carbon budget for NG if regulations include mandates for ongoing improvements that incentivize development and deployment of additional emission control technologies.

5.4 Methods

Methane leakage can be described in two ways: as the mass of methane released over a period of time ($MtCH_4$/yr), or as the proportion of produced NG is lost to the atmosphere before delivery (% leakage). The latter ratio unit is more convenient for monitoring, but converting from absolute to proportional terms can be challenging and controversial because it requires attributing emissions to the NG industry as well as dividing early emissions from well completion over the estimated lifetime production of a well. A simple method of conversion is to allocate measured methane emissions to the electricity sector using ratios from official inventories, then divide annual emissions by gross production values from the same year. This rough estimate will overestimate lifetime leakage rates in years with a large number of new wells (such as in 2008), but is tractable and yields a useful estimation.

To convert absolute levels from top-down studies that measure overall atmospheric levels of methane, we first divide that into fossil sources versus biogenic sources such as cows or anaerobic decomposition. Miller estimated that 45% of overall 2008 methane flux in North America originated with the natural gas industry with a range of uncertainty of 32-58% (Miller, Wofsy et al., 2013). Next the fossil portion of emissions needs to be divided further by fossil industry. The 2013 EPA inventory of 2011 emissions estimates 60% of fossil CH_4 emissions come from the natural gas industry, with the remainder divided between coal (26%) and oil (13%) (EPA, 2013b). Of the NG industry methane emissions, the EPA estimates 20% of those come from distribution infrastructure in urban areas with the remaining 80% coming from field production, processing, transmission and storage. If we combine these ranges of uncertainty, then 15 – 28% of methane emissions originate with the natural gas industry upstream of electric generators, with an expected value of 22%.

All methane emissions were modeled as a variable aspect of NG consumption, that is: $methaneEmissions = \frac{leakageRate}{1-leakageRate} NGConsumption$. This formulation would not be appropriate for a micro-level study where initial plumes of methane during well completion are not uniformly distributed over the well's production. However, this is a reasonable approximation for a macro-level study over a long time frame because new wells are a function of long-term aggregate consumption, and their construction will be spread out over time. From a long-term planning perspective that makes investment decisions rather than evaluating a fixed investment portfolio, all emissions become variable rather than being divided into fixed and variable components.

We used the SWITCH model to identify least-cost electricity grid investment trajectories that could meet an emissions cap and provide reliable electricity. SWITCH was originally written at the University of California Berkeley by Matthias Fripp (Fripp, 2012) then expanded by a larger team into the version used here (Nelson, Johnston et al., 2012; Mileva, Nelson et al., 2013). This version of SWITCH is formulated as a linear program that minimizes the net present value of costs of delivering electricity over the entire planning horizon. It includes a detailed representation of every power plant currently online in WECC, as well as detailed geographic and temporal representations of 6940 potential renewable sites, the large majority of which are wind and solar. Its investment choices include all major types of traditional thermal power plants as well as renewable plants, storage, and transmission. In this study, we imposed an additional emissions adder for natural gas consumed by the electricity sector based on assumed leakage rate and methane's 20 year global warming potential. See supplemental for a more detailed description of the model and data sources.

The electricity load profiles used here include a large amount of efficiency measures as well as electrification of fuel-based heating and vehicles, and are based off prior work on economy-wide pathways to meet emission targets (Wei, Nelson et al., 2013). These scenarios do not include demand response because we don't have cost projections for implementing them. However, demand response would have similar impacts as battery storage because the both effectively move energy between times of day without producing emissions.

In the base scenario, central station solar costs \$2.42 / W in 2016 and falls roughly linearly to \$1.89 / W in 2050. In the cheap solar scenario, central station solar costs follow SunShot trajectories starting at \$1.69 / W in 2016, falling to \$0.95 / W by 2020 then holding steady (US Department of Energy, 2012b).

In this version of SWITCH, the power and energy capacity of batteries are independent decision variables which allows the model to optimize the duration of storage. In the base scenario, battery storage costs \$0.94 / W and \$0.33 / Wh in 2016 and decline linearly to \$0.77 / W and \$0.27 / Wh in 2050. In the cheap storage scenario, battery storage costs \$0.66 / W and \$0.16 / Wh in 2016, decline linearly to \$0.46 / W and \$0.045 / Wh in 2020 and remain constant through 2050. In both of these scenarios, CAES costs \$0.76 / W and \$0.019 / Wh in all years.

In most of these scenarios, the lifetime of all gas plants was 20 years. This is based on a California state figure (Klein, 2010), but many other sources estimate 30 year lifetimes. An additional sensitivity extended the lifetime of all gas plants to 30 years, which imperceptibly changed the base case results.

5.5 Epilogue

This research project updated the results from Chapter 3 by placing limits on the extent to which replacing coal with natural gas can achieve emission reductions in the 2020-2030 timeframes. If methane leakage rates are between 2 and 3% as most national-level studies have suggested, the use of Gas CCGT generation as baseload drops by 24-55% in 2020 and 46-67% in 2030 in the base case scenario, relative to no leakage. If the NG industry takes greater action and achieves leakage rates in the range of 1% by 2020, the use of Gas CCGT generation as replacement for coal can actually grow by 7%, relative to no leakage.

The broad conclusions from Chapter 4 were not affected by leakage. Under leakage, cheap solar still reduces costs and increases solar deployment. Unsurprisingly, cheap solar also mitigates the cost impacts of leakage, especially if accompanied by cheap storage. The primary benefit of BECCS was to providing carbon offsets, which effectively relax the emissions cap and reduce system costs. This primary result holds true when leakage is considered. If a modest amount of carbon offsets were obtained from BECCS, resulting in a gross emissions cap of 70%, there is little interaction with leakage. If large amounts of carbon offsets are obtained from BECCS, resulting in a gross emissions cap of 35%, the cost impacts of leakage will be more pronounced in 2040 and 2050 because the weak cap enables a larger amount of NG under zero leakage relative to other scenarios. However, the availability of carbon offsets still reduces overall system costs in most timeframes.

6 Extending Switch

The preceding chapters primarily focused on results we obtained from using Switch-WECC to study mitigation pathways. This chapter discusses the process of reproducing and extending the Switch model and highlights some methodological advancements that I led.

When we first obtained a copy of Switch, it was a rough collection of code, notes, a small database, and some example run directories. It comprised the code, datasets and lab notebooks that accompanied a fresh dissertation. Several key steps were written as snippets of code written in multiple languages that users needed to read, understand, then paste into the appropriate environment. This ad-hoc format had been useful for Matthias as he had finished his dissertation, but it was not ideal for a small team of interdisciplinary graduate students who wished to reproduce and extend cutting-edge research. This model could be extremely valuable, but using it effectively required broad and deep skillsets, while the scope of work necessitated a scalable team rather than a single individual.

Over the course of several years, we automated and streamlined the code and databases, added functionality and scaled up the geographic scope. Reducing the manual steps required for reproducing research reduced the learning curve for many collaborators without prohibiting them from gradually mastering more skills over time. While there is still significant room for improvement and standing issues of usability and a steep learning curve, we reduced the magnitude of those problems. I led the following methodological advancements to Switch during this process.

1. Improved usability, reproducibility and data management
2. Modeled Renewable Portfolio Standards
3. Tracked carbon intensity of electricity
4. Improved the temporal resolution of dispatch by a factor of 122 in a secondary validation stage
5. Improved timepoint sampling methodology
6. Improved feasibility of solutions
7. Assessed impact of imperfect foresight

Throughout this process, I attempted to employ an agile development approach where we started with a minimal working version that we iteratively add features to, testing functionality at each step. Agile methods generally have lower debugging complexity than a monolithic approach where a significant amount of work is performed in between test or evaluation cycles. Other key goals were reproducibility, computational tractability, accessibility to collaborators, and ability to produce robust and meaningful results that provide technical or policy insights.

6.1 Usability, Reproducibility and Data Management

To start this endeavor, I first learned as much as I could about the model's formulation from Matthias (the original author) while we were at Berkeley together for two months. This interactive handoff period was crucial because it would have been quite difficult to reproduce his work from his notes alone. The software architecture consisted of three main layers: a database, a model defining an optimization problem, and an optimizer.

A structured database contained descriptions of the existing grid, projected loads, projected renewable energy potential, costs, and new projects that could be built. This had been manually compiled from diverse information sources and involved many steps of calculations and transformations which were relatively well recorded. Separate databases were constructed to store the results from each run, and were not linked to each other or the original inputs database. All databases were implemented with Free and Open Source Software (MySQL). Getting data into or out of the databases required opening mysql and bash command prompts and pasting a series of commands from a notes file.

The model defined input parameters, decision variables, constraints, an objective function in terms of mathematical relationships. The model consisted of a set of AMPL files that translated a series of input files into a linear program written in a standard machine-readable file format for the optimizer to solve. The optimizer read the linear program compiled by AMPL, identified an optimal solution, and wrote a solution file. The optimizer (CPLEX) was also proprietary software, and included binary code for interfacing with AMPL. The model also read the optimizer's solutions and exported them into human-readable results. Execution involved opening AMPL in a working directory and pasting a series of commands into the prompt. The files that comprised the model were licensed as open source, but the language it was written in (AMPL) was proprietary software with an expensive license.

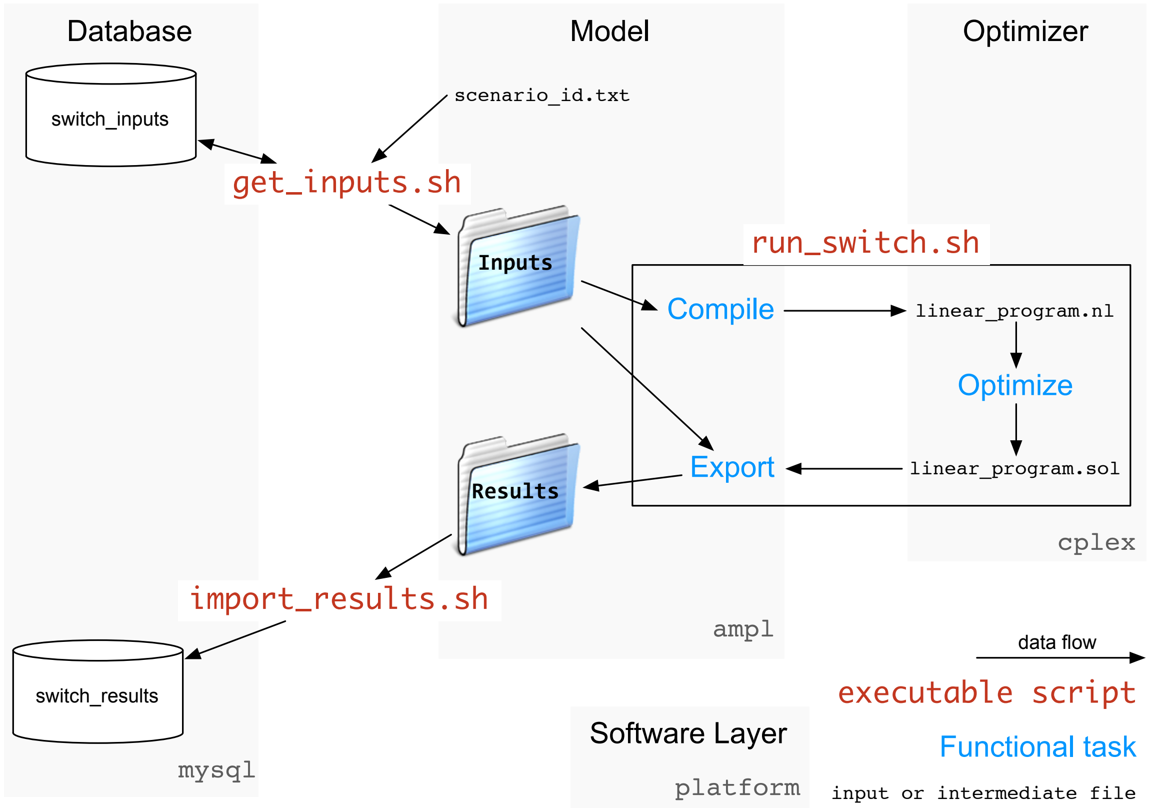


Figure 6.1 Software layers of Switch depicting workflows of data processing after I streamlined the model.

My second stage of Switch work transitioned from understanding what was present to improving its usability. After I replicated runs manually from Matthias's notes, I rewrote his notes into self-contained scripts whose execution could be easily reproduced or automated. A particular run would include a snapshot of the entire codebase, inputs and results to ensure reproducibility of that run. The shell scripts *get_inputs.sh* and *import_results.sh* formed "glue code" between the database and model layers and included features to establish a secure database connection. The shell script *run_switch.sh* would manage all the tasks needed to convert inputs to results: compiling an optimization problem in a standard machine-readable .nl format, optimizing the problem with CPLEX and monitoring the process, and exporting the machine-readable solution into human-readable results. This script was written to work either on a stand-alone computer or with a job scheduler on a high-performance cluster environment and included features to exit AMPL before calling CPLEX to free up memory, and to monitor system resources used by CPLEX during optimization.

The overall model required users to interact with a minimum of three computer languages (SQL, Bash and AMPL), plus a working knowledge of linear programming, electric power systems, climate policy, economics and financing, as well as Geographic Information Systems. While Bash was not my ideal automation language from a technical capabilities standpoint, more collaborators understood this language better than technically superior alternatives such as Perl or Python because they needed a minimal understanding of Bash to navigate the Linux command line. While most collaborators had difficulty understanding the entirety of these bash scripts, they could readily use them and could successfully edit them most of the time.

The separation of database interaction from model execution allowed researchers to conduct analyses by manipulating files and not even interacting with databases. This proved useful to reduce the learning curve and made it easier to put together quick sensitivity runs that only involved changing a few parameters in input files. This separation helped mitigate the tension between fully documenting experimental steps and rapidly conducting exploratory experiments, a tension that is common in scientific software development.

As we began editing and improved the code, I led the team to use a code repository to track our changes. A code repository is essentially a specialized advanced backup system that keeps a full history, with a clear record of every major edit that includes timestamp, contributor name and commit message. This allowed us to track the development of the code, revert to earlier versions if we found we introduced a bug or discover that we made a wrong turn. When we had difficulty understanding some portion of code, we could review the history to learn who wrote it so we could ask them for an explanation. Initially we used subversion for this, but eventually migrated to git which made forking and merging easier.

As we scaled up the geographic scope and increased the diversity of scenarios and experiments, the database layer grew increasingly important. As the volume and complexity of the databases grew and more people contributed, it became important to optimize database performance via indexing and add integrity checks such as unique key constraints to help maintain quality control and reduce errors. Defining primary keys using a small number of columns (ideally stored as unsigned integers) increased speed significantly, as did insuring that tables that needed to be joined stored their keys in identical formats. To reduce the risk of human errors, we set up automated backups and used database privileges on user accounts to limit access for new collaborators so they could read everything, but could only create or modify tables in a sandbox database. After they grew comfortable with basic commands and were less likely to make mistakes, we gave them full permissions, and encouraged them to backup individual tables before they edit them, and always stage and test their work before applying it to the production database. Adding additional unique constraints ensured that contributors could not add duplicate records by mistake. More integrity checks would have been useful but at the time, mysql did not support foreign key constraints and had limited support for other sanity checks. As we worked with the model and made mistakes in data integrity that led to bad outcomes, we inserted additional checks into the core switch model to detect and report common errors early in the process to simplify diagnostics.

We also had several versions of inputs that were often mutually exclusive, but we couldn’t just overwrite old data without harming our ability to reproduce existing runs.

The existing ad-hoc solution of defining a new table or database for each new set of assumptions or scenario was not scalable because it required editing interface code for each version, a step that often led to human errors of overwriting results or using the wrong inputs. Also, duplicating entire databases for each variation would have required constantly buying and maintaining new hard drives and disk arrays to keep up with new scenarios and code developments.

To deal with conflicting sets of data such as two estimations of generator costs, I added an extra index column such as *gen_cost_scenario_id* to each relevant table, so that different cost estimates could co-exist in different rows, as long as they had distinct values for *gen_cost_scenario_id*. I repeated this pattern for other tables such as load scenario, timepoints sampled, generator availability, fuel costs, etc. A master scenario table would specify particular **_scenario_id* values for each table, uniquely identifying which combinations of inputs to use for the overall scenario. I adapted this solution to unify the results databases by adding a *master_scenario_id* column to each table in the results database. Merging all of the results into a single database allowed us to perform data mining, and directly compare and contrast diverse scenario to gain new insights. Overall, extra indexing columns largely addressed the problem of naming proliferation and its impact on code maintenance and query complexity.

As we generalized and expanded the model from California to the entire Western Interconnection, we encountered difficulties in using legacy tables to store new data or support new features. We needed to adapt our database schema while preserving backwards compatibility to ensure we could reproduce our earlier work. Our code repository let us keep snapshots of code from every point in time, but there was no corresponding functionality for databases, aside from duplicating the database. I addressed these issues using a hybrid approach of escalating impact. First, I considered whether adding new data columns to existing tables could support new requirements. New index columns could have changed how old code retrieves data, but new data columns would be ignored by old code as long as it specified each column by name, rather than using an asterisk * to select all columns. Sometimes new functionality required more extensive restructuring – changing index columns, deleting columns, or changing data values. In those cases, I recommended defining a new table with the suffix _v1, _v2, etc and updating the entire database to use the new table. When the number of changes got too large or unwieldy, we would duplicate and rename the database to have a suffix reflecting the version number. Over time our schema stabilized and the need for new versions slowed so that in the end our input database was named switch_wecc_v2_2.

While these practices mitigated some scalability and version problems, they did little to address difficulties of data ingestion and processing. I encouraged all collaborators to use best practices of reproducibility with good record keeping, archiving and scripting when they imported and processed data. In ideal circumstances, we would have scripts that recorded every step from downloading data from public websites, to importing it, performing Quality Assurance / Quality Control (QA/QC), processing it, and combining it with other data to fit Switch requirements. Under ideal conditions, it would be easy for other labs to independently replicate our work, review our data processing steps, or adapt them to use newer datasets or improved methodologies. Unfortunately, most of the data we retrieved was messy and required significant manual steps of QA/QC. Errors included typos in plant names, mistakes about when daylight savings time takes effect, rare numerical instabilities in solar calculations as the sun approached the horizon, and many others. We kept notes about corrections as best we could, but overall, the QA/QC process could not be fully automated. Some corrections of individual rows could be scripted if we had already imported raw data into the database, but some steps were often easier to perform using more interactive tools such as spreadsheet or Google Refine. Additionally, several steps of data ingestion and georeferencing generation plants, loads and transmission lines relative to load zones could most expediently be completed using manual interactive techniques. Sometimes this involved two people reading off plant codes and inspecting printed maps, sometimes it involved one person working for hours interactively in ArcGIS which did not support recording workflows. As much as possible, we performed geospatial processing in PostGIS (an open source GIS database) which fully supported scripting and reproducible workflows. In the future, we would ideally exclusively use PostGIS and automated workflows so that load zones boundaries could be redrawn easily and new data could be readily incorporated as it becomes available.

Other parts of data processing could at best be semi-automated. For example, calculating solar electric potential for thousands of sites across WECC using multiple photovoltaic and solar thermal technologies required scraping an insolation database of historical gridded solar radiation data for North America from the State University of New York and combining it with a separate dataset of historical weather from NOAH that used a different grid and an entirely different file format. The combined data had to be written into a third file format that could be read by SAM, a simulation engine for evaluating solar potential. SAM is interactive software designed by NREL that has limited scripting capability in its own unique language. Compiling our entire solar database required running on the order of 40,000 SAM simulations. Parallelizing and automating this task was essential for completing it in a timely manner. In theory all of that could have been automated with SAM's scripting language, but in practice the SAM was not stable enough to reliably complete more than 50 simulations without crashing, and SAM was not available for a Linux command line that could be spread over a cluster or fully automated. This necessitated writing a layer of code in AppleScript that could initiate, monitor and restart SAM instances. I ultimately deployed about 10 instances of this across half a dozen computers in headless mode, and babysat it over the course of several weeks. I managed to make that task semi-automated, but until the SAM developers make their model available via batch processing or headless API's, those calculations cannot be fully automated in a robust manner. Realistically, the best we can hope for is semi-automated workflows.

Finding quality data sources for the entire region we wished to model proved difficult. We initially used whatever sources were most convenient or were of highest quality, but these data sources were often specific to individual utility service territories or states. We rapidly realized that heterogeneous data sources were not scalable to the larger region we wished to model, and modeling the entire interconnect with its diversity of renewable energy potential and loads was important to identify cost-effective renewable energy portfolios, enable resource sharing and to avoid reshuffling problems where high-polluting plants are built just outside of the model's boundaries. We sought federal datasets as much as we could, relying heavily on Federal Energy Regulatory Commission (FERC) filings and Energy Information Agency reports. Ultimately both of these sources proved insufficient and we were forced to subscribe to commercial services that provided geolocations for generators and transmission lines. These proprietary datasets were quite expensive, and came with extensive restrictions on how we used and redistributed the data. After extensive negotiations, the vendor allowed us to graduate from using their interactive website to providing us with GIS shape files that we could programmatically access, and they allowed us to redistribute aggregated views of the data to accompany publications. Access to some datasets also required filing formal requests with FERC to get security clearances, a process that took over six months to complete. Overall, the data we could obtain was rarely in the format or granularity we required, and making it usable required extensive processing and/or estimation. The DOE currently has an initiative to make data more accessible and support community repositories to archive curated datasets, so these difficulties may decline in the future.

A secondary data processing problem emerged as we delved deeper into geospatial processing. The MySQL database software that was a legacy from Matthias's prototype had very limited support for storing or processing GIS data, and we needed extensive support. PostgreSQL (aka psql) was another open-source database with extensive GIS support with its PostGIS extensions. Although both platforms are based on the SQL language, they have enough idiosyncratic differences that most MySQL scripts need to rewritten to run on PostgreSQL and vice-versa. By the time we realized this, we had invested extensive efforts into MySQL databases and supporting scripts; porting them to PostgreSQL would be a significant undertaking that we could not justify in the short term, given the pressure we had to produce results and publish. As a work-around, we developed patterns of importing all GIS data into PostGIS, exporting data from MySQL to PostGIS through files for processing or aggregation, then passing data back to MySQL through another series of files. Each transfer and processing step required manual intervention, so fairly little of the geo-processing could be fully automated or easily reproduced. This break between our primary results and our GIS information was also a significant impediment to generating maps of our results, which were an important communication tool. Towards the end of our major group collaboration, Jimmy Nelson made significant strides in compiling a dataset of the entire US and Canada into PostgreSQL, but he was unable to finish this before he graduated. If we had to do this over again, we would exclusively use PostgreSQL for its GIS support, international language support, stability, data integrity features and overall scalability. MySQL scaled very poorly as we increased the volume of data and number of scenarios, eventually forcing us to transition to a fork of that project (MariaDB) that could provide stability and reasonable speed with large datasets.

6.2 Modeling Renewable Portfolio Standards

Renewable Portfolio Standards (RPS) have been one of the most widespread policy devices for supporting clean energy in the United States, so representing them in Switch was quite important. I developed a method of modeling RPS within Switch in a general manner that can accommodate a diversity of RPS definitions and requirements – even different jurisdictions disagreeing on a definition of "renewable". This method tracks renewable electricity as it moves through transmission and storage systems on its journey from generators to loads, a requirement for "bundled renewable energy credits" (more below). This method assumes that electricity flows can be perfectly managed to distinguish renewable and non-renewable power via use of a transportation model rather than an AC power flow model where energy mixes thoroughly and it becomes much more difficult to attribute which generators actually provided electricity for a particular load. A transportation model is often a useful approximation because current policies typically allow the use of non-renewable generation to help move or reshape renewable energy before it reaches load. To support cases where mixing is relevant for analysis, I also developed a post-facto method for tracking the carbon intensity of energy across the network assuming complete mixing at each node. This second method could also be used to track the "actual" renewable energy fraction at each node rather than the contractual renewable energy fraction.

A Renewable Portfolio Standard is legislation that requires a certain amount of electrical energy to be produced by renewable generators. In the United States where the validity of global warming has been publically debated, RPS policies have been adopted more widely and earlier than emission targets that are specifically designed to mitigate global warming. RPS appeals to more perspectives (energy independence and economic development, not just global warming), and has consequently garnered a broad base of political support. RPS policies by themselves do not ensure low-emissions because they can co-exist with large amounts of coal, but they are still important as an initial transition to a sustainable electricity system.

In the US, most RPS standards have been set at the level of states and use a variety of language and eligibility criteria. For example, northeastern states chose to define large hydropower as renewable while western states chose to define it as non-renewable. There's the occasional oddball like Nevada's inclusion of "waste tires" as a renewable energy source (Nevada Legislature, 2009), but the large majority of newly built renewable facilities are wind and solar. States also frequently have carve-outs for specific technologies, distributed generation, or limits on out-of-state generation.

RPS accounting typically works like so: When a qualifying renewable generator produces 1 MWh of electricity, it is issued a *Renewable Energy Certificate* (REC). The REC is distinct from the underlying electricity. If the REC is sold separately from the underlying electricity, this is called an *Unbundled REC*. If the REC and electricity are sold together, it is called a *Bundled REC*. Each utility that is obligated to meet an RPS ultimately provides a certain amount of RECs to their regulatory agency. Most states require that most RECs be bundled, ensuring that their energy supply actually shifts to more renewables and their policy doesn't just subsidize renewable generators elsewhere.

Bundled RECs are more difficult to model than unbundled RECs because of the added complexity of tracking energy as it moves through transmission networks and differentiating it from non-renewable energy. As electricity portion of a bundled REC moves through the transmission network, it suffers energy losses so that 1MWh of produced energy may only serve 0.92MWh of load. If the electricity took a longer path through the transmission network or passed through storage, then the amount of load served would decrease further due to transmission losses. However, the REC associated with that electricity is not de-rated to reflect transmission losses according to typical RPS accounting practices. This inconsistency is potentially problematic because the goal is set relative to load served, while credits are awarded based on gross production, and if transmission losses are significant, the goal won't be necessarily be met in a meaningful way.

The basic methodology is as follows: Two or more categories of energy are defined, and each generator is assigned a category. In this simple case, this will just be "renewable" and "non-renewable". Each generator injects energy into the network at a bus, and the amount of each category of energy at each bus is tracked. Separate transmission decisions are made for each category, with the constraint that the sum of all energy types traveling on a transmission line not exceed the line's installed capacity. Each load has separate decision variables for consuming electricity and consuming RECs. A constraint forces the sum of REC consumption for a load within an investment period be greater than or equal to the RPS requirement. Storage can also be included, if desired, using a similar method where separate accounts are kept for each category to track incoming energy, energy in storage, and outgoing energy. However, existing RPS policies typically do not allow bundled RECs to pass through storage, so storage tracking is not included in the current implementation in Switch.

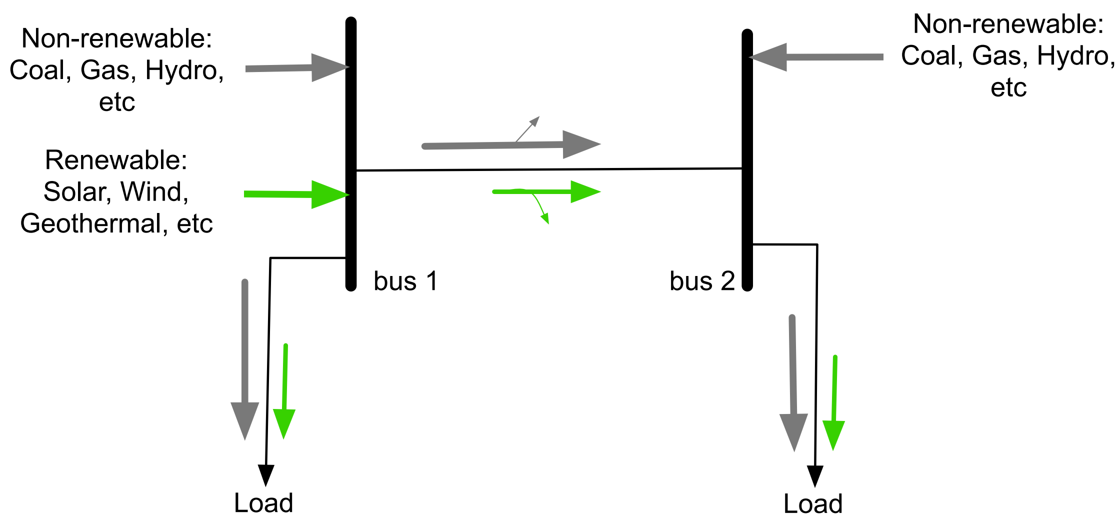


Figure 6.2 Simple illustration of Renewable Portfolio Standard tracking.

In this simple illustration, bus 1 receives renewable and non-renewable energy from local generators. Some energy is transmitted to bus 2, and some energy is consumed by local load. Most of the energy sent through transmission is delivered to Bus 2, but some of it is lost along the way. Bus 2 receives both categories of energy via transmission as well as non-renewable energy from local generators. All of Bus 2's incoming energy goes towards serving load. Each bus's load is served by some renewable and some non-renewable energy.

Mathematical model simply requires keeping separate thermodynamic accounts for renewable and non-renewable energy on each bus, transmission line, and consumption for each point in time. To prevent energy from being reclassified as it moves through the network, I defined a conservation of energy constraint separately for each energy category at each bus and timepoint.

$$Generation_{c,t} + TransmissionIn_{c,t} - TransmissionOut_{c,t} - ConsumeEnergy_{c,t} = 0$$

$$\forall \; c \in ENERGY\_CATEGORIES \, , t \in TIMEPOINTS$$

Transmission capacity limit is enforced via a constraint defined for each transmission line and timepoint that forces the overall energy transmitted in all categories to be less than or equal to installed capacity:

$$\sum_{c} TransmissionOut_{c,t} \leq Installed\_Tx\_Capacity$$

$$\forall \; t \in TIMEPOINTS$$

RPS goals are enforced with a constraint defined for each bus and categorical goal:

$$\sum_{t \in TIMEPOINTS} ConsumeEnergy_{c,t} \geq Goal_{c}$$

Load requirements are enforced with a constraint defined for each bus and timepoint:

$$\sum_{c} ConsumeEnergy_{c,t} \geq load_{t}$$

This simple formulation is easy to understand and implement, but it does not reflect how RPS accounting ignores transmission losses for bundled RECs. This simple formulation can be used if you can assume that policies will be updated eventually to address this inconsistency/loophole or if you can claim transmission losses are relatively negligible. In the general case, more categories of energy can be defined to represent generators such as hydro or used tires, which will be considered as renewable by some states and non-renewable by others. Each category of energy would be tracked separately, and each load can specify which categories count towards their RPS targets – which can be used to generate constraints that only sum across permitted categories. This method also can describe technology-specific carveouts by defining secondary constraints that require a certain amount of RECs come from specific categories.

For several years, we found the simple formulation acceptable and we used it extensively in our research. We found that RPS policies alone were insufficient to meet climate stabilization goals because least-cost RPS systems led to large amounts of renewables and coal. Our analysis indicated that either a carbon tax or price was necessary to push coal out of least-cost solutions. When we included a carbon cap policy in our models, we saw that RPS became irrelevant in the long term because renewables were the least-cost zero-emission energy source. In the near-term, RPS could be a binding constraint that kept gas from completely taking over the system, but in the long-term, the RPS became a non-binding constraint.

As a policy mechanism, RPSs are valuable for appealing to a wide political base, for boot-strapping renewable markets, and starting to shift to a sustainable trajectory. If extreme RPS goals are used, like Hawaii's recent goal of 100% renewables by 2040 (Representatives, 2015), RPS mechanisms could remain a valuable mitigation tool for decades to come. However, the tracking requirements associated with bundled RPS add a significant computational burden to optimization, and if other stronger policies cause bundled REC targets to become non-binding constraints, then dropping them can greatly simplify optimizations.

Tracking and differentiating energy through the transmission network significantly increases computational complexity by effectively doubling the linkage decisions in the network. Other policy tools add little direct computational burden (unbundled RPS goals, installation goals, other production targets and even emission caps) because they do not require the same level of tracking. Completely ignoring transmission losses for RECs in this linear programming framework would be difficult without either increasing ambiguity or adding significant computational complexity.

You could tracks RECs as separate decision variables that are linked to the underlying energy, but this would increase ambiguity as the energy moves through the network and accumulates transmission losses, causing the relationship between energy and REC to become less straightforward. Say the energy sent over transmission is described as $EnergyRecieved_{1\to2,c} = lineEfficiency * \ EnergySent_{1\to2,c}$ where $EnergyRecieved_{1\to2,c}$ is used for calculating $TransmissionIn_c$ in the conservation of energy equations. The movement of RECs could be described as $REC_{Recieved_{1\to2,c}} = REC_{Sent_{1\to2,c}} = EnergySent_{1\to2,c}$. Assuming that all energy and RECs are produced at bus 1, then the limits on energy ad RECs available are well defined as $EnergyConsumed_{2,c} \leq lineEfficiency * \ EnergySent_{1\to2,c}$ and $RECConsumed_{2,c} \leq EnergySent_{1\to2,c}$. The two consumption variables can be linked as $RECConsumed_{2,c} * \ lineEfficiency = EnergyConsumed_{2,c}$ in this case. The problem arises when RECs and energy arrive through different paths and accumulate different line losses along the way because a single $lineEfficiency$ cannot adequately describe their relationship as their values diverge and become more varied. You could lift the requirements of joint consumption, but then the RECs would not remain strictly bundled. Also, if the transmission decisions remain tightly coupled to energy, then the full value of RECs will not be able to make multiple hops through the network because the maximum amount of energy available at the second node for transmission will be less than the RECs available.

Another approach is to track each energy transfer directly from source to ultimate destination as a single decision, but that would greatly increase computational complexity. Since the above approach works with a single hop, you could reformulate the transmission module to directly track energy from origin to ultimate destination by defining every possible acyclic path and setting up a decision variable for each path. The transmission limit constraints for each segment would need to consider all paths that use that segment, along with the line efficiency of every segment upstream on a given path. Writing this is do-able, but the computational impact of adding so many linkages to the transmission network would be quite significant.

After several years, my colleagues led a reformulation of the RPS module to be computationally faster, less accurate, and to avoid imposing transmission losses on RECs within an RPS compliance region and between adjacent RPS compliance regions. Their method used a hybrid of the above approaches, choosing to track REC consumption separately from energy consumption and to keep separate conservation equations for RECs and underlying energy. In transmission and generation, renewable energy is used as a direct proxy for RECs. Their approach lacks a constraint to force REC consumption to stay synchronized with energy consumption. This effectively unbundles RECs when they arrive close to their ultimate destination. This could be problematic in theory, but in practice, the method produced reasonable results. They only differentiated transmitted energy source category if it crosses RPS compliance regions; otherwise it is aggregated to reduce linkages. Their conservation of REC constraint considers REC consumption and generation within a compliance region, as well as transmission between compliance regions, without applying transmission losses to any terms. This allows RECs produced locally or in neighboring regions to be consumed without incurring transmission losses, but RECs produced beyond adjacent regions will incur transmission losses up to the point where they enter adjacent regions. Key equations of this alternate formulation follow.

Conservation of REC is defined for each REC compliance region *r*, timepoint *t* and energy category c. The RECs consumed in a compliance region need to be less than the sum of local generation of that energy category across all buses within the compliance region, plus the sum of that category of energy sent into the compliance region (ignoring transmission losses), minus the sum of that category of energy exported from the compliance region:

$$
\begin{aligned}
&ConsumeREC_{c,r,t} \\
&\qquad \le \sum_{b \in r} LocalGeneration_{b,c,t} + \sum_{b2\ not\ in\ r} EnergySent_{b2 \to b,c} \\
&\qquad - \sum_{b2\ not\ in\ r} EnergySent_{b \to b2,c}
\end{aligned}
$$

The three energy terms on the right hand side of the equation serve as proxies for RECs, which are not explicitly tracked. The term $EnergySent$ is only indexed by energy category *c* for transmission lines that span RPS compliance regions to reduce linkages in the transmission network; transmission lines within an RPS region lack the index *c*. Similarly, the *ConsumeEnergy* variable is no longer indexed by energy category, and the conservation of energy equations sum across all energy categories rather than being specified separately for each category. The RPS enforcement equation relies on the $ConsumeREC_{c,r,t}$ variable since *ConsumeEnergy* is no longer indexed by energy category. In this formulation, RECs are only sent along with energy, so the portion of RECs associated with transmission losses are not available for export and must be either consumed locally or lost. This formulation allows RECs to be consumed locally while the underlying energy is exported, but this event is unlikely to occur in most circumstances because the energy exported would no longer be classified as renewable and would not have that added value. This event could happen in timepoints where local renewable energy production is in excess of local load, but those sorts of errors would be likely restricted to individual timepoints; the annual REC and renewable energy consumption would likely be reasonable if that much renewable energy was being produced. Overall this method provides approximations that are generally reasonable and result in substantial decreases in runtime and memory requirements.

6.3 Tracking carbon intensity in a well-mixed network

Tracking energy as it moves through a transmission network is a modeling convenience that can be useful for establishing contracts or policy. But in reality, tracking energy in a network is as difficult as tracking a drop of water in an ocean, and some analyses need to reflect that reality where energy tends to be well-mixed. For example, some people are quite interested in locational carbon intensity of electricity indexed by time, and people could be interested in understanding the fraction of electricity that is renewable in each timepoint and location. To support those types of cases, you may calculate those values for a given dispatch plan with the assumption of well mixing. I will describe the basic method for carbon intensity calculations, but it is readily adaptable to other metrics such as renewable energy fraction.

The basic method requires a complete dispatch plan for every point in time that includes the energy generated at each bus, the emissions associated with that generation, the consumption at each bus, and the transmission decisions that move energy between busses. For a given point in time, you start by topologically sorting a graph representation of the transmission network so that each bus that has no imports is assigned to level 0, each bus that only imports from level 0 buses are on level 1, each bus that only imports from level 1 or level 0 buses are on level 2, and so on until each bus is assigned a topological level. The carbon intensity at each level 0 bus is readily calculated by dividing its local emissions by its local generation $CarbonIntensity_b = \frac{TotalLocalEmissions_b}{TotalLocalGeneration_b}\ \forall\ b\ \in Level_0$. All electricity exported from level 0 buses are assigned this carbon intensity and have a known amount of embedded emissions

$EmbeddedEmissions_{b0\to b1} = CarbonIntensity_{b0} \cdot EnergySent_{b0\to b1}$. When calculating embedded emissions, it is important to use the energy sent rather than the energy received which has transmission losses deducted. The carbon intensity at level 1 buses is readily calculated from their local generation and embedded emissions $CarbonIntensity_b = \frac{TotalLocalEmissions_b + \sum EmbeddedEmissions_{*\to b}}{TotalLocalGeneration_b + \sum EnergyRecieved_{*\to b}}\ \forall\ b\ \in Level_1$. This procedure is repeated for each subsequent level. It is worth noting that the net emissions at any bus should subtract the embedded emissions that are exported to other buses. Overall, this method is very computationally tractable and requires two passes through the dataset: first to topological sort the transmission graph, second to assign carbon intensities. It is relatively simple to explain and should be accurate as long as transmission dispatch forms a Directed Acyclic Graph (DAG) and the impact of storage is not significant.

If storage becomes a significant part of the system, it will effectively shift emissions between timepoints. If dispatch is strictly linear with a beginning and end, this problem can be treated in the same manner as described above, but with storage deposits and withdrawals forming links in the graph that connect different timepoints. As long as each timepoint's transmission dispatch forms a DAG, their linear time series will also form a DAG. Problems with this simple approach may arise if either transmission forms cycles or if dispatch time series are treated in a circular manner, where the last timepoint in a time series is treated as preceding the first timepoint in that time series. A circular treatment is used by Switch to avoid edge effects when accounting for storage or ramping, with the assumption that a time series describing a representative day will likely have similar days on either side, so that energy stored in one evening can be released the next morning. Switch also does not require that transmission dispatch form a DAG, and cycles in transmission graphs are not uncommon especially in hours with excess renewable generation. Since transmission lacks a variable cost in the Switch model, many inefficient transmission plans are equally optimal when excess energy is available. A general solution for this is to use an iterative method to estimate net emissions at each node, then propagate estimated emissions through transmission and storage arcs to update emission estimates for the subsequent iteration. This method is described in more detail below.

Carbon intensity of electricity is calculated with an iterative method that propagates embedded emissions along transmission lines according to a given dispatch schedule. Emissions are repeatedly propagated until an additional iteration alters the net emissions less than one percent. The diagram below illustrates a simplified dispatch schedule where storage's energy balance occurs over two timepoints. Notice that energy can flow through storage from timepoints 1 to 2 (node A) and can flow backwards from timepoints 2 to 1 (node E). Storage conducts an energy balance over a typical day that repeats, so E's storage schedule can be interpreted storing energy in the evening and releasing it the next morning.

Our RPS implementation divides power into renewable and non-renewable stocks that remain distinct from generation source, through transmission, storage and intermediate load areas to its final destination. For purposes of tracking the stocks of power and embedded emissions, we can consider dispatch of non-RPS power completely separately from RPS power. The diagram illustrates the dispatch of non-RPS power.

The following terms are used in these calculations:

P_{gross} : The total power available to a node that can be consumed or sent out. For nodes representing a load area in a given hour, P_{gross} is calculated as the sum of locally generated power, power received from transmission, and power received from storage. For nodes representing a storage project over a day, P_{gross} is calculated as the total power released in a day. Because of inefficiencies, this will be less than the power received in the same day.

P_{net} : The power available to an hourly load area node after some power is sent out. This term is not relevant to daily storage nodes.

$P_{x\text{->}y}$: Power sent from node X to node Y in a given hour.

E_{gen} : Direct emissions from generators in a load area in a given hour. This term is not relevant to daily storage nodes.

$E_{x\text{->}y}$: Embedded emissions sent from node X to node Y along with power in a given hour.

E_{gross} : The sum of direct emissions from generators and embedded emissions received by a node.

E_{net} : A load area's net emissions in a given hour (gross emissions minus all exported embedded emissions). This can be calculated as $E_{gross} \bullet P_{net} / P_{gross}$ This term is not relevant to daily storage nodes.

With this formulation, E_{gross} and $E_{x\text{->}y}$ are defined in terms of each other. The embedded emissions $E_{x\text{->}y}$ is calculated as a percentage of the gross emissions of the source node: $E_{x\text{->}y} = E_{gross,src} \bullet P_{x\text{->}y} / P_{gross,src}$ Conversely, gross emissions are calculated as the sum of direct emissions and all embedded emissions received. We sidestep this circular dependency by making initial estimates, then iteratively recalculating each term with the prior round's estimates. Initially E_{gross} is E_{gen} for hourly load area nodes and 0 for daily storage nodes. Similarly, $E_{x\text{->}y}$ is initially set to 0. At each round, we also calculate the difference in E_{net} and look for convergence. We do not let the process cycle through more than 100 rounds and will exit early if the sum of the differences in all of the nodes' E_{net} between rounds is less than 1% of the total emissions for the day's graph: $\frac{\sum|E_{net}-E'_{net}|}{\sum E_{gen}} < 0.01$. In practice, most scenarios reached convergence in 10 rounds, and the slowest convergence required 19 rounds.

The final carbon intensity of electricity in a load area is calculated as the sum of the net emissions across RPS and non-RPS categories divided by the sum of the net power across the same categories.

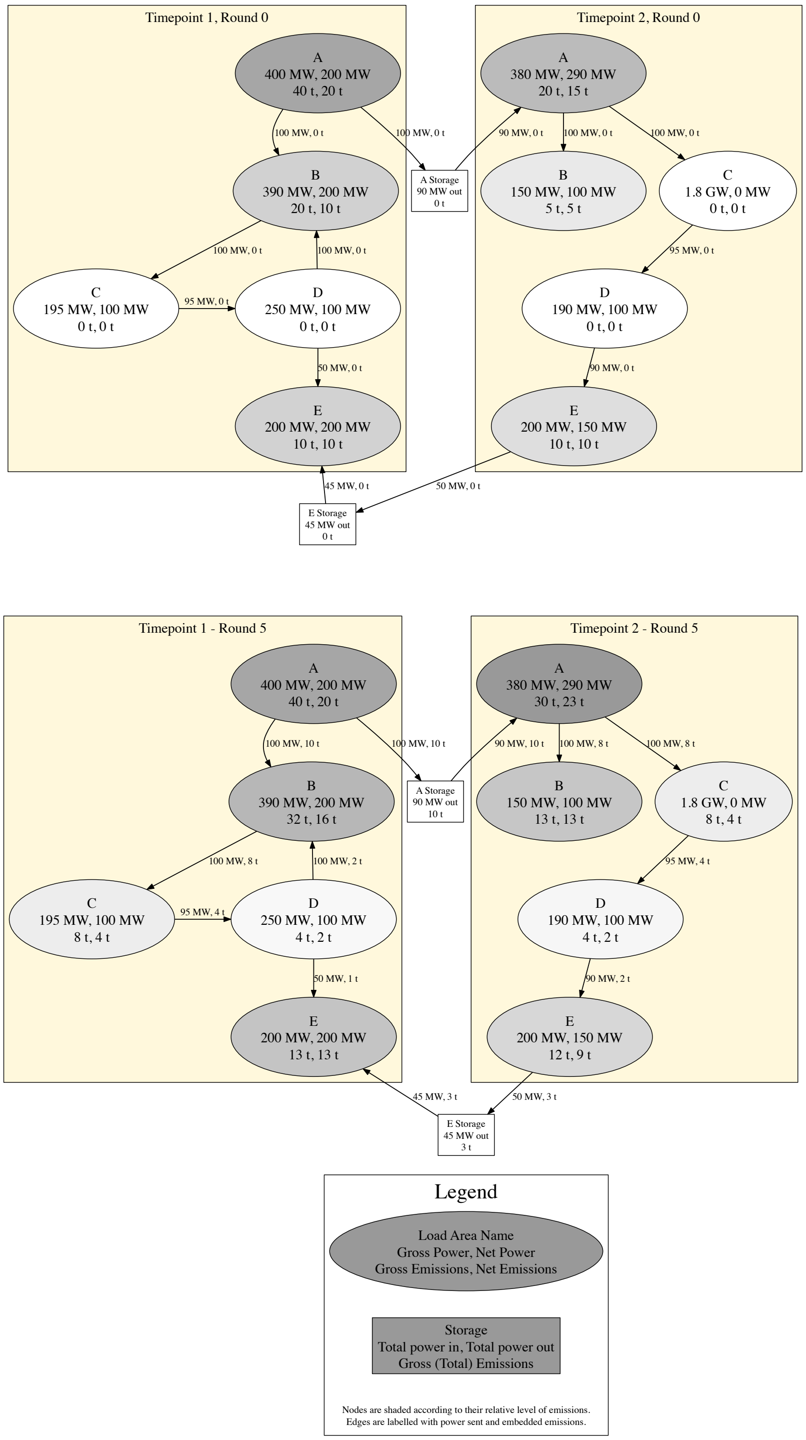


Figure 6.3 Example dispatch graph of non-RPS power over a day. The top panel shows initial estimates and the bottom panel shows final estimates after 5 rounds. Gross, net, and exported emissions may not add up in the diagram due to rounding the values in the labels (e.g. Load area D, Timepoint 1 in round 5).

6.4 Dispatch verification

The Switch-WECC model estimates the costs and feasibility of day-to-day operations using a relatively small number of timepoints (144 per investment period). These timepoints were selected to include dates with median energy demand and dates with peak power demand. However, this sampling method could not guarantee these timepoints would include peak net demand (load minus intermittent generation) because the build-out of renewable generation and their resulting contribution to net load was not known before the optimization is run. Also, the timepoints for a given date are sampled at 4-hour intervals which tends to underestimate the hour-to-hour variability of net load. Increasing the sample size improves the estimate of operational costs and feasibility, but it also greatly increases the size of the optimization problem. The size of the problem was roughly proportional to the square of the number of timepoints because additional timepoints would increase the number of decision variables (columns in the constraint matrix) and the number of constraints (rows in the constraint matrix). We gradually increased our sample size until we hit computational limits where our jobs on high performance computing clusters would time out after one week and/or the commercial solver we use (CPLEX) would crash. Further increasing the size of a single large problem is not a feasible or scalable approach.

Some point after I began working on Switch, I realized we were merely reporting results for the subset of timepoints that we optimized against, rather than using a distinct set of timepoints. In the vocabulary of machine learning, this amounts to reporting performance with a training set instead of a test set, a practice that can lead to overfitting and overoptimistic results. Computational limitations forced us to sample just 576 timepoints out of a dataset of almost 70,000 timepoints. It was entirely possible that certain renewable projects could appear to produce more power during the sampled timepoints than their annual average, and that the optimization was biased towards projects with that sort of sampling error. Without a secondary evaluation, we had no idea what costs, reliability or emissions would results from dispatching an optimized portfolio on a larger time series.

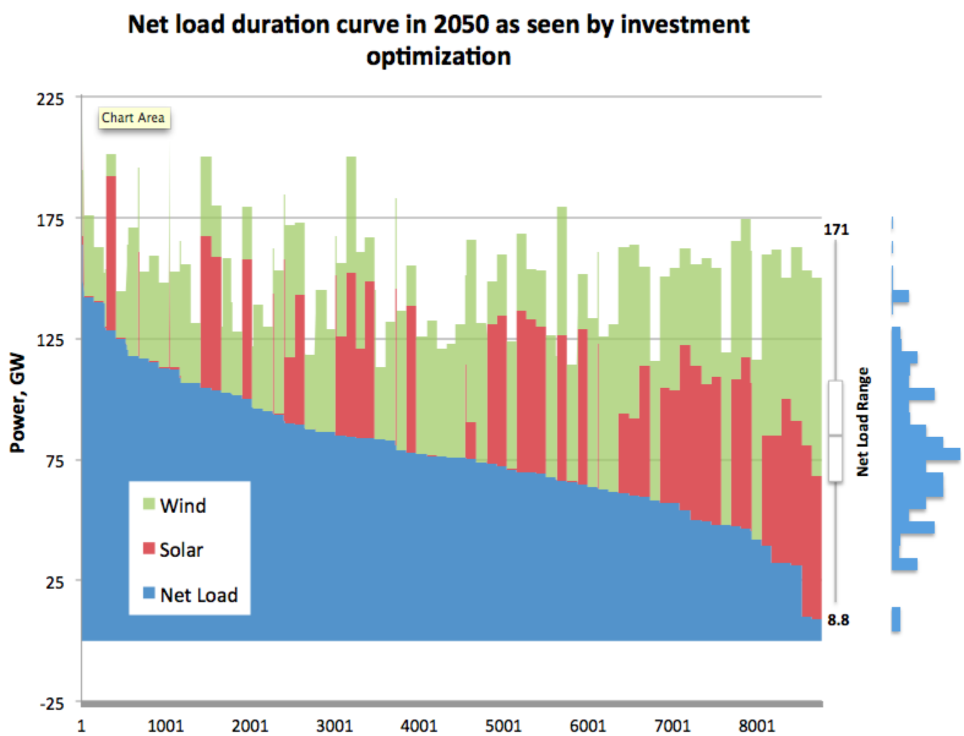
To address this, I wrote a "dispatch verification" module to tests an investment plan against all available timepoints that include unanticipated combinations of load and renewable energy output. This module revealed capacity shortfalls that could be large, and that these capacity shortfalls could be addressed without significantly changing costs. We also found that overall energy costs were quite robust against a larger time series, but that emissions tended to be underestimated. I used the instrumentation provided by this module to improve our sampling method to reduce systematic bias, to reduce capacity shortfalls, to evaluate the impacts of imperfect foresight, and to reduce emission overruns. More detailed descriptions of those improvements are provided in subsequent sections. The remainder of this section describes the dispatch verification module and problems that it revealed.

The primary optimization incorporates a modest amount of operational detail to endogenously reflect integration requirements as well as the capacity factors (and economics) of fossil plants. This resolution is relatively unique for a capacity planning model, but is quite important for rationally planning high-renewable systems so we can understand how the grid needs to be built to accommodate large shares of renewable generation. In an ideal world, this operational modeling would be extremely detailed and represent all of the timescales that might present challenges for a high-renewable system. In practice, computing hardware limits the amount of detail we can include in a model while maintaining tractability. After we compiled all of the datasets for WECC and ran simulations, we found that 576 timepoints evenly spaced across the study were about as many as we could include in the investment optimization and while reliably maintaining computability.

The dispatch verification module operates after the primary investment optimization is complete. This module altered the primary model to only focus on dispatch decisions by fixing investment decisions, a standard operation in mathematical programming languages. The module would load investment decisions from the primary optimization, then load a fresh time series of electricity demand and renewable energy production data, and finally optimize a dispatch-only problem using the same formulation for operations as the primary model. In cases where installed capacity is insufficient to meet load and the optimization problem is infeasible, I enabled a recourse decision of installing additional peaker plants of simple cycle natural gas combustion turbines, then compile and optimize the new problem. To reduce total computational time and take advantage of parallel computing in a cluster environment, I divided the dispatch time series by historical date, so each day of dispatch can be compiled and solved independently. To combine recourse decisions into a coherent feasible solution, I took the maximum installed capacity of new peakers plants across dates, grouping by load zone and period. This will not guarantee an optimal solution, but the costs we examined do not shift significantly from the original solution so it is close enough to optimal to be useful.

The first working version of the dispatch module that we used for our first two peer-reviewed publication (Nelson, Johnston et al., 2012; Wei, Nelson et al., 2013) could detect and address capacity shortfalls, but would not produce meaningful costs or emissions. I eventually traced those bugs to problems in the weighting of timepoints in dispatch that was causing large errors in the relative weight of variable and fixed costs. Once I corrected the timepoint weighting, the electricity costs and emissions from the dispatch module passed our quality control tests.

Figure 3 below shows two net load duration curves in the 2050 period of a control run: one is made of the 144 sampled timepoints seen by the primary optimization and the other is made all 17,376 timepoints that we have historical records for. The sampled dataset has a smaller range of net loads and is blockier, but has a generally similar shape. This net load duration curve is inspired by a load duration curve, but timepoints are ranked by net load (system load minus intermittent renewable output) rather than load.



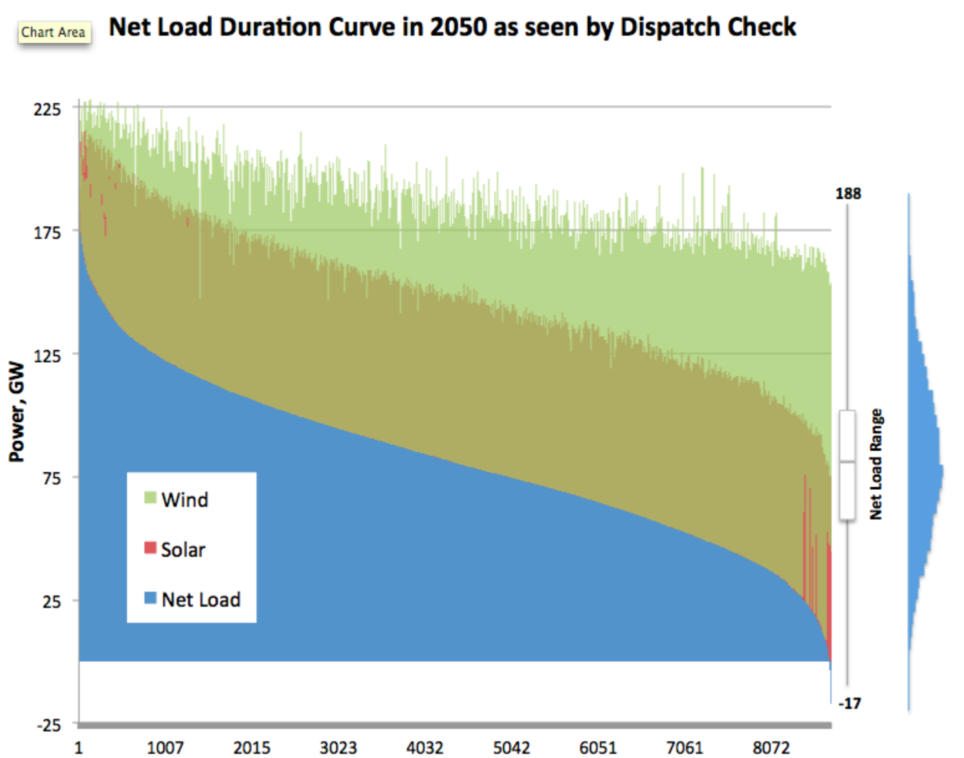


Figure 6.4 Net load duration curves as seen by the primary optimization and the dispatch verification. The net load is shown as a blue bar at the bottom of the stack, and the contribution of wind and solar are stacked above it. The width of each bar reflects the weight of that timepoint. This depiction shows that timepoints from median days are

weighted approximately 30 times greater than timepoints from peak days. The primary optimization uses 144 timepoints with varying weights while the post-optimization dispatch check uses 17,376 timepoints with equal weights. The contributions of wind and solar are difficult to discern in the lower panel due to Excel's rendering of a dense dataset. The right side of each figure shows the distribution of net loads as a bar-and-whiskers plot based on quartiles and as a histogram. Negative values of net load seen in a few hours in the lower figure indicate that renewable energy supply occasionally exceeds load and would need to be curtailed.

The higher value of net load in the complete set of timepoints resulted in a maximum capacity shortfall 13.9 GW in the 2040 investment period for this control run (data not shown). These infeasibilities almost exclusively occurred just after sunset in late July and August in later investment periods that have high solar penetration: air conditioning loads are still relatively high, but solar energy is unavailable. These infeasibilities can largely be attributed to insufficient sampling. Our standard method of sampling every 4 hours usually does not capture the hour after sunset that has the peak net load.

Most investment plans generated by the current version of SWITCH-WECC had capacity shortfalls on the order of 15 GW in later periods - around 6% of peak load. Cost projections were generally within 2-3% of the expected value, even after installing additional gas turbine peaker plants to avoid capacity shortfalls. Emissions in the last two periods are generally 20-30% above the emissions target, which is mostly due to increased consumption of natural gas. We are still examining results to better understand the emission story. It could be that the primary optimization overestimates the total amount of renewable energy produced, underestimates hour-to-hour variability of net load and emissions that come with starting up additional units or running some units at partial load, or that significant amounts of renewable energy has to be curtailed because it exceeds local demand and transmission to other areas is constrained. Answering these questions is part of my ongoing work.

We have used a simple iterative approach to deal with these capacity shortfalls, where we identify the future timepoint that has the largest capacity shortfall in the complete dispatch check, update the investment problem to include the extreme conditions, then re-solve the investment optimization. We encountered these capacity shortfalls in scenarios that we needed to finish a paper (Mileva, Nelson et al., 2013) and were looking for a quick fix that was also defensible. The capacity shortfalls vanished within 3 or 4 iterations for all of the scenarios we applied this method to, and scenarios with lesser projections of solar penetrations required fewer iterations. With the exception of one problematic scenario, the small increase in problem size did not create computational infeasibilities. As a standard solution, this method is far from perfect. It increased the total runtime from around one week to three or four weeks. We could have potentially bootstrapped this process by including timepoints that were known to create infeasibilities in prior scenarios, but some team members were uncomfortable with that approach because it gave no guarantee of capturing peak net load and they believed it would be hard to defend. Moving forward, it would be valuable to have a method to include more timepoints and ideally reduce total runtime.

6.5 Reducing emission overruns

The problem of emission overruns proved more difficult to address than capacity shortfalls. Our initial approach to emissions overruns were to set a more stringent cap in the investment optimization so that the overall emissions from dispatch would be close to the actual emission cap we wanted. This allowed us to complete a few more research projects, but overall was unsatisfying for several reasons. It required iterating through several carbon caps, and different scenarios in the same study often required different starting caps, which made them harder to directly compare. The emission overruns tended to arise from renewable energy shortfalls that prompted a higher capacity factor for spare gas capacity (including peaker plants). An optimized portfolio that could actually meet the cap would presumably install more renewables to avoid the need for extra gas, or at least install a larger amount of combined cycle gas plants that would have a lower emissions factor than simple cycle peaker plants. These emission overruns were particularly troubling for the natural gas leakage study because the extra use of gas capacity could double the overall emissions when leakage rates were high. I studied this problem and evaluated several methods over the years, and eventually managed to reduce the magnitude of this problem significantly.

One of our first theories was that the dispatch verification might be choosing the wrong loading order for fossil plants. One problem of dividing the dispatch problem into individual days is that annual constraints such as carbon caps cannot be directly represented. The lack of such a constraint could adjust the loading order of plants to dispatch more coal and less gas, which could explain some of the emission overruns. To ensure the proper loading order was used, I dualized the annual emission cap constraint so that I could represent it in each decomposed dispatch problem. I accomplished this by exporting the dual value of the emission cap constraint from the primary problem and applying unit conversions to convert it into a carbon cost that varied by period. I rewrote the carbon cost formulation to vary by period, imported these values into the dispatch problems, and disabled the carbon cap constraint. I verified that additional emissions costs produced correct loading order of fossil generators, but this reduced the magnitude of the emissions overrun by an insignificant amount.

The next promising theory focused on the discrepancy in total renewable energy between the primary optimization and the dispatch verification. I thought if we understood the sampling error in the primary optimization, we might be able to reduce it by changing out sampling method. Towards this end, I calculated the sample error mean annual energy for each renewable project – that is, the mean energy for sampled timepoints minus the mean energy for all timepoints – then normalized this value to a z-score by dividing by the standard error of the mean that accounts for sample weighting using a standard statistical formula (Cochran, 1977). The equation for the normalized sample error was $\frac{\bar{x}-\mu}{SEM}$. I evaluated this using a weighted SEM and a non-weighted SEM and obtained qualitatively similar results. This normalized form allowed me to readily compare sample errors across projects of different sizes and technologies. Figure 6.5 shows the un-smoothed probability distributions of these standardized sample errors for all 13,444 utility-scale renewable projects in our master database. This shows that the sample error had a systematic positive bias for central PV, but the sample errors for other technologies is unbiased.

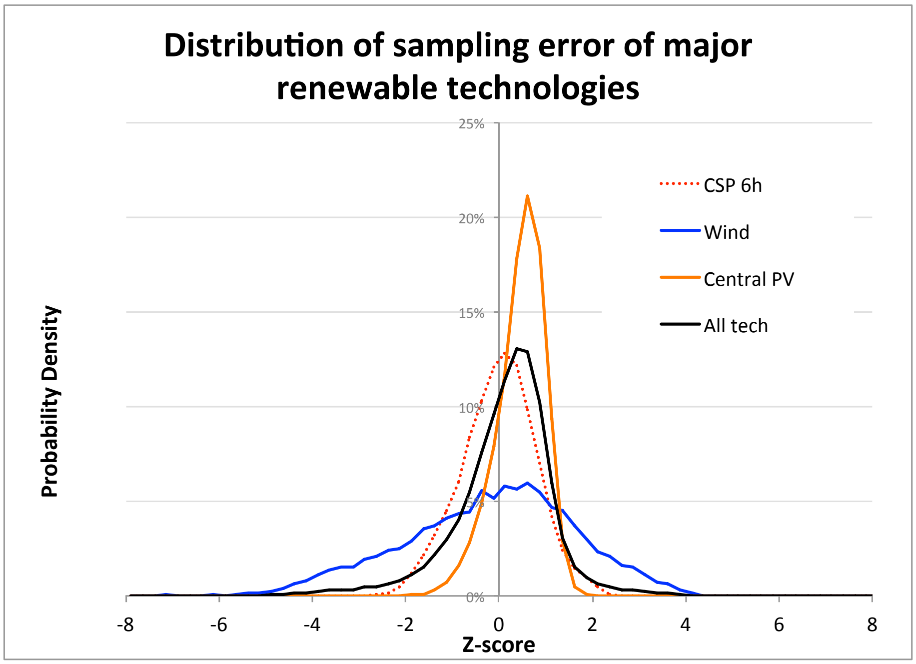


Figure 6.5 Distribution of the initial sample error of mean annual energy produced by utility-scale renewable energy projects. Overall, renewable projects showed a positive bias, but this was almost exclusively due to the bias of central station solar.

Having isolated the systematic bias to central station solar PV, I investigated the impact of sampling methodology on this bias. By convention, we had sampled median days at four-hour intervals starting at midnight GMT. This starting time was arbitrary and could result in the inclusion of greater or fewer daylight hours over the course of a year across the roughly 7500 central PV sites in WECC. I created three additional sampled sets that started at 1, 2, and 3am to determine if another time was better. The results indicated that a 12am GMT start time resulted in the largest bias and a 2am start time effectively removed this bias (Fig 6.6). Updating the sampling methodology to reflect this improved the emissions problem by a few percent, but failed to address the bulk of the problem.

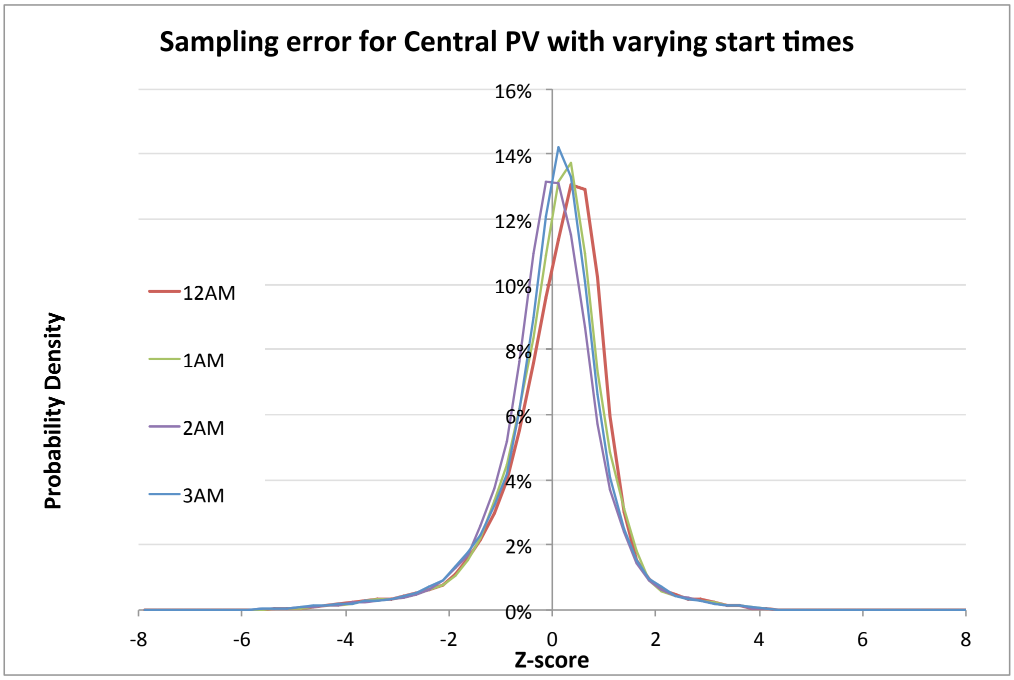


Figure 6.6 Bias in sample error of Central PV energy production is dependent on which hour of day sampling starts. Starting at 2am GMT effectively eliminates this bias, while the initial approach of starting at 12am GMT resulted in the largest bias.

To explore this issue further, I recalculated a normalized sample error for projects that the model chose to install, and overlaid sample error of installed projects with sample error of all potential projects (Fig 6.7). I found the optimization preferentially built projects where the sample error overestimated the renewable energy. For this particular run, this preference resulted in a 6% shortfall in renewable energy. It makes sense that the optimization would tend to choose a renewable site with a positive sample error over a site with a negative sample error, all else being equal. And given the large number of renewable sites to choose from, this preference added up to a significant problem. The simple solution would be increasing the number of data points to reduce sample error, but that was not computationally tractable.

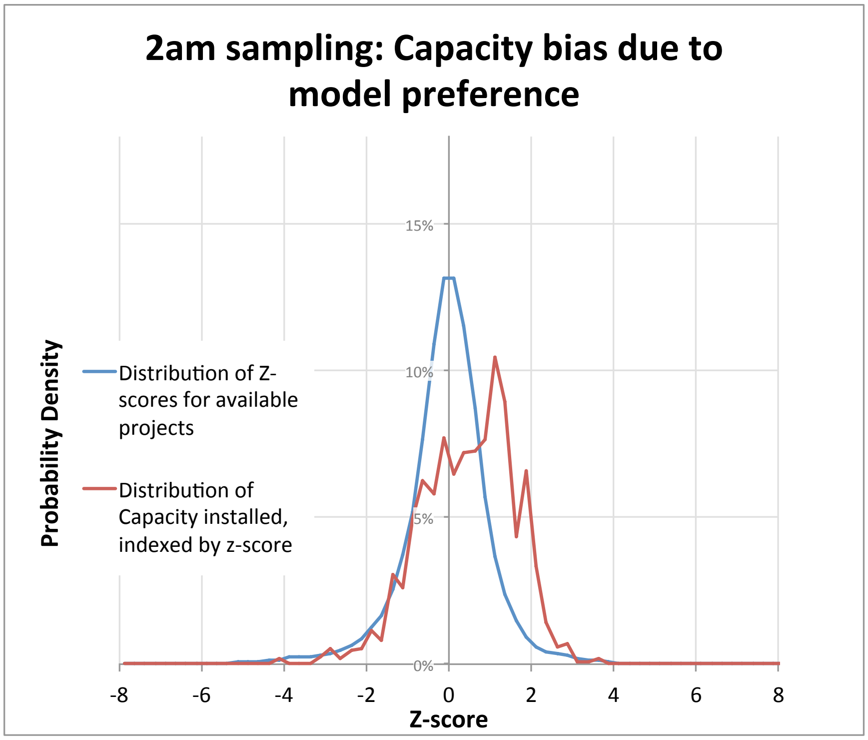


Figure 6.7 After removing initial sample bias from all available projects, the optimization is biased towards projects whose sample error overestimates their annual energy production.

My next step was to drill down further in the data to identify when these renewable energy shortfalls were happening and which technologies were contributing to them. I thought if I had a better understanding of the problem, I might be able to think of a targeted solution. A colleague who had examined dispatch data in detail for her own research (Ana Mileva) had anecdotally noticed some large capacity shortages in August when the primary optimization tended to over-estimate wind power in scenarios where wind dominated renewable generation. She thought I might be able to address the problem by including an additional high-stress day and giving it more relative weight. I was intrigued by this idea, but wanted to have a better understanding of the data before I went forward.

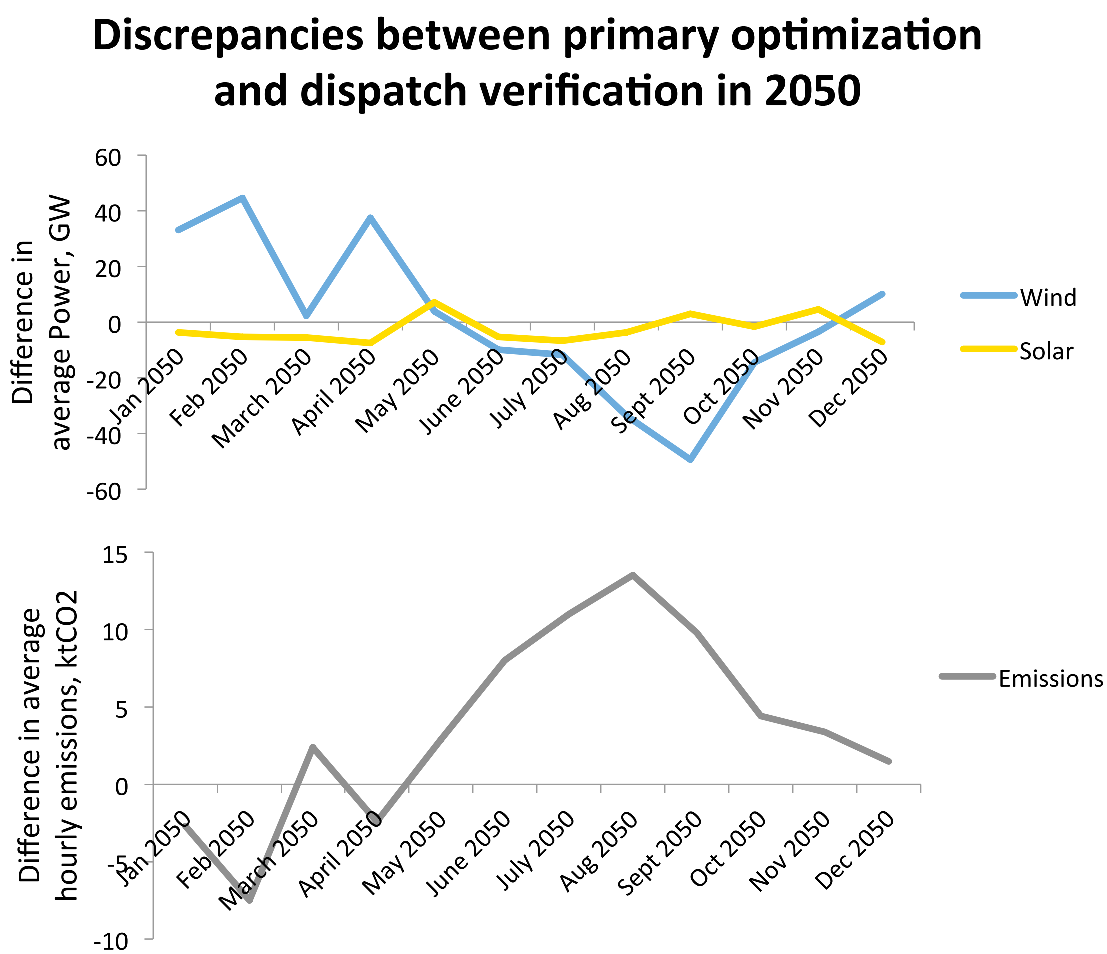


Figure 6.8 Comparing differences in average hourly renewable power and emissions between the primary optimization and dispatch verification of a control run in 2050, the period with the highest emission overruns, revealed that wind power was significantly underestimated in winter and spring and overestimated in summer while solar tended to be slightly overestimated over most of the year. Emission overruns were correlated with renewable energy shortages, but were also determined by other factors.

Directly comparing grid operations between primary optimization and dispatch verification proved to be a challenging and tedious informatics exercise, but eventually I obtained the requisite view (Fig 6.8). During the process, I realized that renewable energy shortfalls were an indirect proxy for emission overruns because overall emissions depended strongly on the emission intensity of the capacity available when the shortfall was happening. For example, if combined cycle gas turbine capacity is available to meet the energy gap, that will yield much lower emissions than if simple-cycle gas combustion turbines is the only available capacity. The results supported this theory. I found that the renewable energy shortages had a rough correlation with emission overruns, but emission overruns also occurred in three months where renewable energy was underestimated (May, November and December). This suggested that focusing more directly on emissions rather than renewable energy shortages could yield a more targeted solution to emission overruns. The data also revealed that while emission overruns peaked in August, they were pervasive throughout the year and an adjustment to August sampling was likely to have limited impacts.

When I compared daily emission profiles between the primary optimization and dispatch, I found that the peak days from the primary optimization had emission profiles much more similar to dispatch than the median days. As you may recall, timepoint sampling is performed in a stratified manner to select two days per month based on projections of load. A month's peak day is selected on the basis of maximum system-wide load in any hour, and the starting hour is chosen to ensure that timepoint with the peak load is included. A month's median day is selected on the basis of daily energy demand being very close to the median daily energy demand of that month. The selection is adjusted to ensure that the same historical date that is used to project demand and renewable power is not selected more than once. This median day is given a weight of roughly 30 times the peak day – actually the number of days in the month minus 1. This strategy results in sampled annual demand that is typically within 0.2% of the annual demand of the complete dataset.

While the peak day had emissions that were similar to or greater than the average dispatch emissions, the daily energy demands of the peak and median days were similar for most months. This suggested a solution where I could increase the weight of the peak day enough for the month to have representative emissions without significantly altering the overall load requirements. This could be written as an optimization for each month whose objective function is to minimize the emission discrepancy. The decision variable is the amount of weight to shift from median to peak day. Constraints are that the resultant sampled load cannot exceed dispatch load by more than 5%, that all final weights remain positive, and that the weight adjustment cannot be greater than the initial difference in weights. For expediency, I implemented this semi-manually in a spreadsheet using an exported database view rather than formally writing it as an optimization. In my initial experiment, I limited this weight adjustment to the five months with the highest emission overruns in 2040 and 2050. I limited the changes because small alterations to an optimization problem have greater chances of success than large alterations, in my experience, and the choice of five months was subjective based on manual inspection of data.

I made a few versions of adjusted problems, some with adjusted weights, some with a few additional dates that had the largest capacity shortfalls in dispatch verification, some with both. Normally these optimizations would finish in 12 hours, but none of these finished in 72 hours, and all progressed at similar rates according to their log files. I let one version run for over 2 months on the lab's fastest server before cancelling it. These results were disheartening and made me thing that decomposition and increased sample size may be the only viable strategy for addressing emission overruns. While working on a near-final revision of the natural gas paper and grappling with finding language to address the large discrepancies without invalidating the results, I decided to budget another 10 hours of my time on a last-ditch effort, and one of the ideas I tried worked well. The viable solution was to limit the secondary optimization to just 2040 and 2050. This entailed loading the initial problem and solution from the primary optimization, updating the timepoint weights, freezing decisions for 2020-2030, compiling a new smaller problem and optimizing it. For the natural gas leakage scenarios, this resulted in a significant improvement. The original formulation resulted in dispatch emissions overruns of 100% under a 0% leakage assumption, while the reweighted formulation only had overruns of 20% (Fig 6.9).

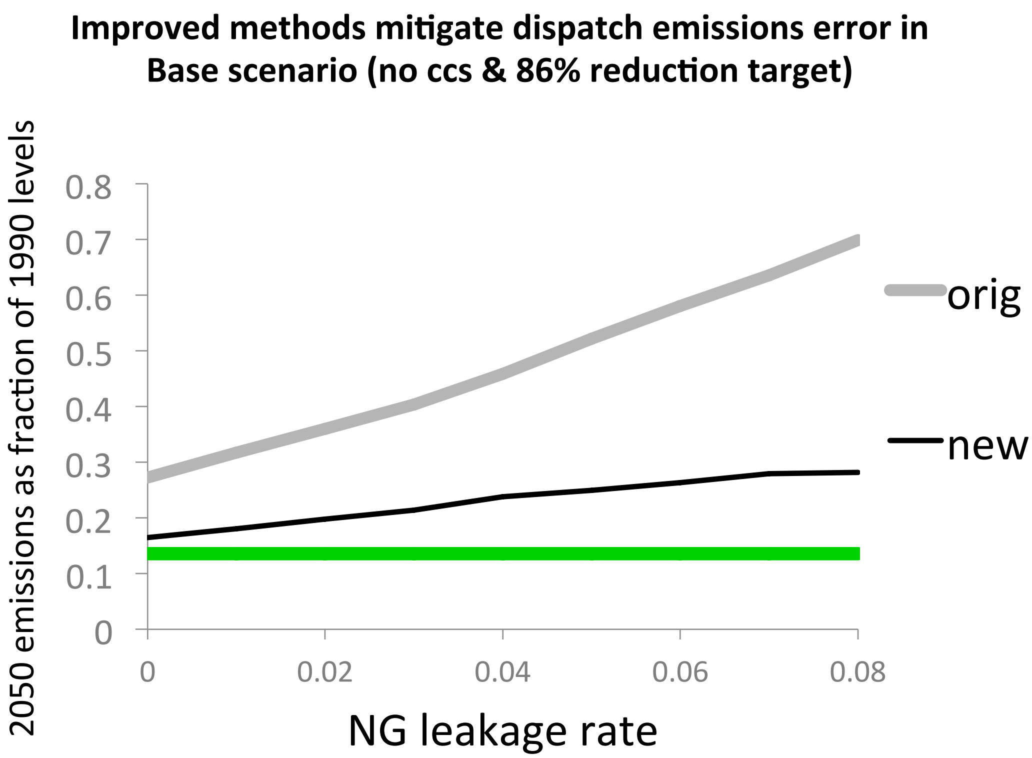


Figure 6.9 Adjusting timepoints weights in 2040-2050 and re-optimizing greatly reduced the problem of emission overruns for the natural gas leakage study.

6.6 Assessing impacts of imperfect foresight

The core SWITCH model assumes perfect foresight even though several key parameters would be better represented as random variables. An "optimal" investment plan with this assumption can result in outages, lower reliability as well as cost and emission overruns if predictions are incorrect. In studies conducted to date, we addressed uncertainty in cost and technology projections by running simulations of several scenarios. This approach generates a set of specialized investment plans (one for each scenario), but does not tell us how well an investment plan would perform under alternate scenarios. Without further work, we do not know if a given investment plan is relatively robust to unexpected situations or not. This approach also does not give us recommendations of what to build today, given the range of possibilities we think tomorrow might bring.

A robust solution to this problem would be to utilize stochastic programming to model all possible scenarios and to develop a portfolio that performs robustly in all scenarios. Unfortunately, this approach greatly increases the computational complexity and would require some form of decomposition to be tractable. Past attempts to implement decomposition within the AMPL implementation of Switch via Benders decomposition and Lagrangian relaxation proved unsuccessful. In retrospect, any decomposition method that is implemented within the primary codebase is bad from a project management perspective. Decomposition is complicated and relies on specialized mathematical techniques that most people are unfamiliar with. Switch already requires a number of diverse specialized skillsets. Adding additional requirements would greatly reduce the number of people that could understand and contribute to the model. Part of ongoing research is re-implementing Switch in Pyomo, an open-source platform that has libraries to automate decomposition associated with stochastic programming and does not impose that complexity on people who are contributing to the core deterministic model.

Still, there are alternate approaches to this issue that are tractable within the AMPL implementation of Switch. It is possible to develop an optimization plan specialized to one scenario and use the dispatch verification module to assess its performance using assumptions from an alternate scenario. In this way, you can assess the robustness of an optimized investment plan. Accomplishing this is relatively straightforward and requires copying input files describing an investment plan from one scenario's directory and input files describing everything else – costs, loads, renewable output, hydro availability, or other assumptions – from a different scenario's directory. Once all of the files are assembled in the dispatch input directory, the dispatch module can assess the portfolio's performance using standard workflows. This methodology is best suited for assessing alternate values of a continuous numeric parameter, and will break down if inputs are qualitatively different, like whether or not new nuclear or CCS can be built.

I used this functionality to assess the sensitivity of the optimization to the choice of discount and finance rates. By finance rate, I mean the interest rate paid on a loan. Initially Switch used the same parameter to describe finance and discount rates, which was consistent with the investment perspective of discount rate as opportunity cost of capital, and assumptions of equilibrium in financial markets such that finance rates on loans would be equal to the average return on investment across a wide portfolio. However, equilibrium conditions are rarely met in the real world and other perspectives on discount rates based on consumer-welfare or intergenerational equity are equally valid and suggest that a smaller discount rate is more reasonable, perhaps even 0. My colleagues conducted an exploratory run where they lowered the finance/discount rate from its default of 7% and got significantly lower energy prices in the later periods. In most scenarios we observe that energy costs increase significantly between 2040 and

2050, and I was curious if this was due to the choice of discount rate. A discount rate of 7% corresponds roughly to a doubling in value every decade, which implies an increased ability to pay. While this can be justified from an investor's perspective that has significant capital and enjoys opportunities for large economic growth, it is ridiculous from most consumers' perspectives and inconsistent with the flat rate of growth in median income over the past four decades in the United States. If the price increases in 2050 were primarily due to the choice of discount rate, we would need to adjust the choice of discount rate and thoroughly explore this issue and the ethical implications.

I rewrote the model to use distinct values for finance and discount rate, then conducted sensitivities on both values. I found that the discount rate had virtually no impact on the electricity costs in any period, but the finance rate had a significant impact in every period (Fig 6.10, 6.11). I used the methodology described above to assess how robust the solution was to the finance rate used in the primary optimization. I found that investment plans were quite robust to the finance rate used in the primary optimization (Fig 6.12). This methodology can readily be extended to other parameters, and should be used if this version of Switch is used as a decision support tool for large capital investments.

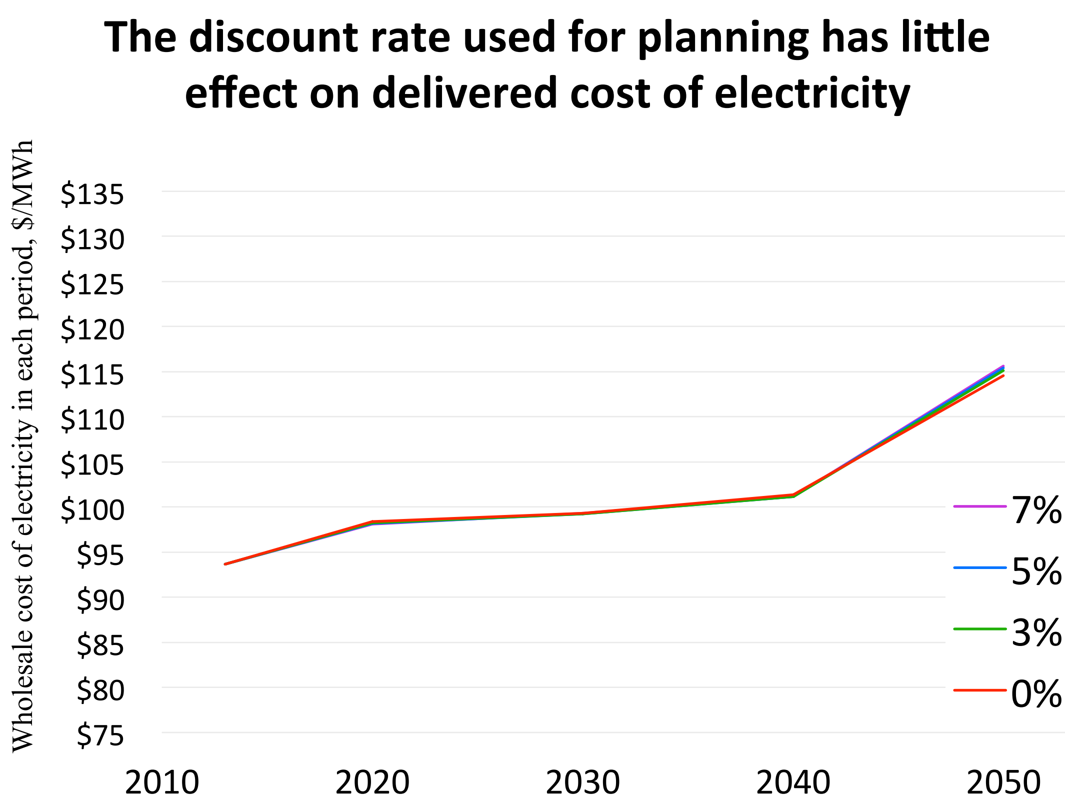


Figure 6.10 A series of sensitivity runs indicate that the choice of discount rate used in planning has very little impact on electricity costs, even over 40 years of discounting.

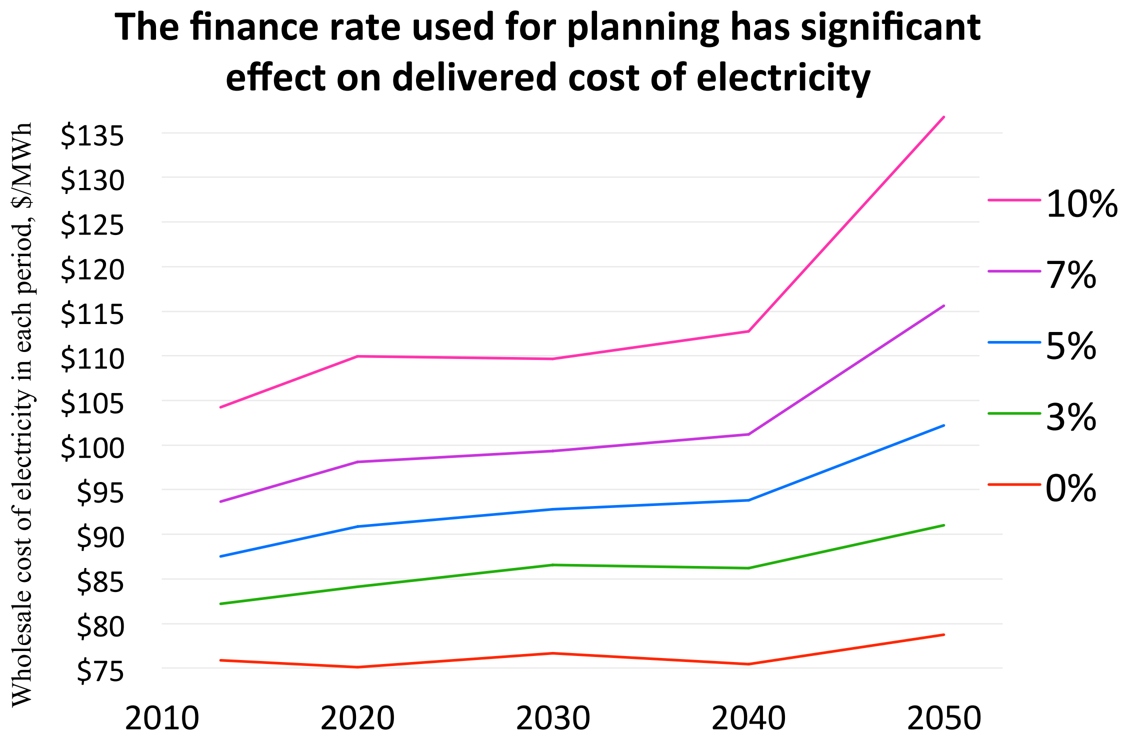


Figure 6.11 A series of sensitivity runs indicate that the finance rate paid on loans has a significant impact on the cost of electricity in all periods.

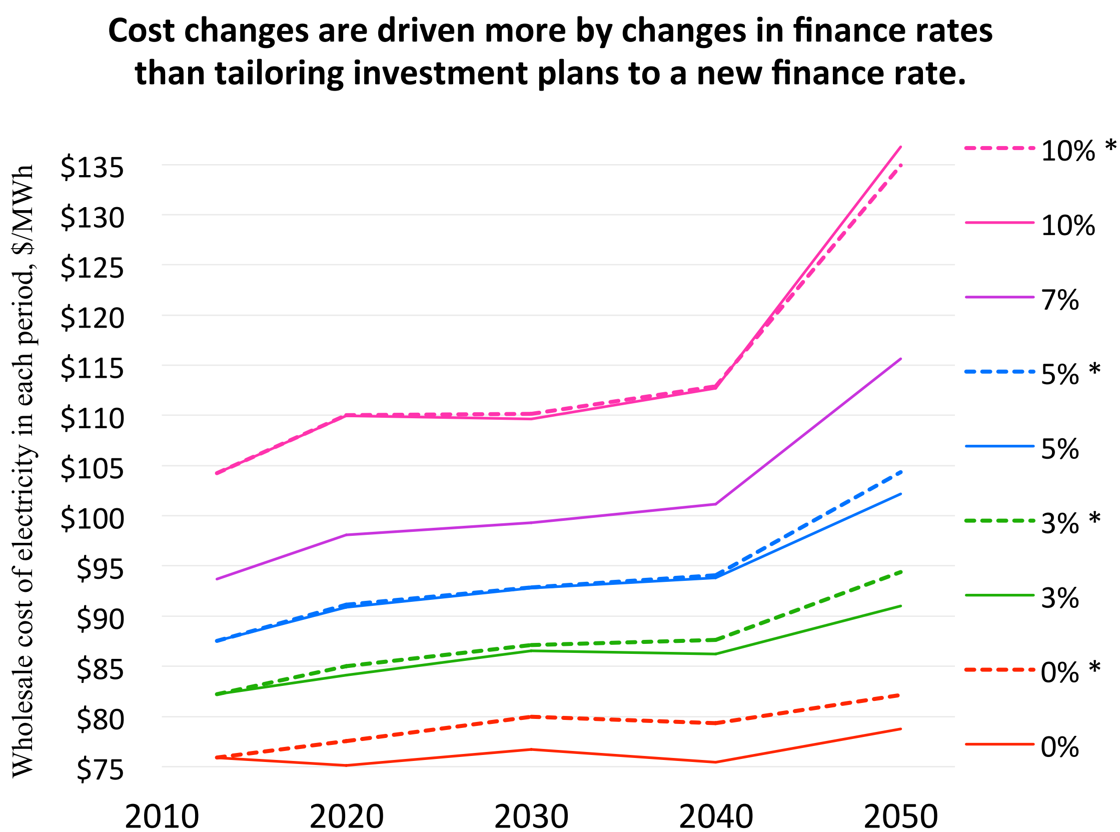


Figure 6.12 A series of robustness tests indicate that an investment plan optimized with a 7% finance rate results in costs very similar to investment plans optimized to alternate finance rates. Each dashed line shows the costs resulting from evaluating an investment plan optimized to a 7% finance rate using an alternate finance rate. The gap between the dashed and solid lines indicate the cost savings from reoptimizing the investment plan to a different finance rate. The fact that the gap is small for small adjustments in finance rates indicates that most of the savings results from lower interest payments rather than a different investment decisions.

7 Discussion

Switch has been successful used as a modeling tool for collaboratively developing emission reduction plans for electric power grids in California, the western US and Canada (WECC), China, Chile, Nicaragua, and Hawaii. It has been used in numerous research publications as well as reports to government bodies and development banks. These efforts have been recognized by the UN during the 2014 Climate Summit (United Nations, 2014). I worked most extensively with the WECC version, and have supported other graduate students develop versions for other countries. This model of open collaborative development of regional models and open source software tools is taking root in Chile (largely due to the efforts of Juan Pablo Carvallo), where the government is sponsoring capacity building and research exchange programs to promote the development and use of Switch-Chile.

Moving forward, there is a need to make Switch more accessible and scalable. Even though Switch itself is open source, it is currently written in a proprietary language and uses a proprietary solver, access to which can cost $10-20k for non-academic users. These costs can be a significant entry barrier to potential users. Switch also currently has a steep learning curve, where ingesting data for a region or setting up a scenario requires extensive database programming, and running Switch requires using a command line interface on a Linux or similar system. Computationally, Switch currently has poor scaling capabilities and has difficulty taking full advantage of high performance computing clusters. To address these problems, I have started porting Switch from AMPL to Pyomo/Pysp, an open source software stack that supports automated decomposition for stochastic programming. This should address the cost and scaling issues. The Pyomo version of Switch is part of my ongoing research, and I am hoping to publish a paper on it this fall.

I am also intending to start a consortium with colleagues and other interested parties to support ongoing development, training and deployment. At this moment, we are receiving code contributions from Berkeley students and alumni, an energy consulting firm and Google. Over the next two years, I am hoping that we can expand our contributor and user base to include additional academics, established energy consulting firms, NGOs, as well as renewable energy institutes from Chile and the United States. There is a growing recognition and institutional support for open collaborative practices for data and software, and Switch is well positioned to flourish in this environment.

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Appendix A. Supplemental material on impacts of methane emissions

Detailed discussion of inventories and emission studies

Official US inventories rely on aggregated emission factors, infrastructure and production statistics, and self-reporting by large industrial emitters. The primary basis of all official inventories is 1996 study conducted by the gas industry and the EPA. Inventories between 1998 and 2010 showed flat methane emissions from the NG sector over time with a modest decline starting around 2003 (Fig 5.1). In 2011, EPA leakage estimates increased by 66% to reflect operational events where the top of a well is essentially opened to allow high-pressure gas at the bottom of the well to push liquids out of the well shaft. These updates were applied retroactively to emission inventories and attempted to reflect changing industry practices during the early stages of the fracking boom. Most of the increase reflected routine liquid unloading in traditional wells to remove groundwater that seeps into wells and restricts gas flow. A smaller portion of the increased emissions reflected the end-stages of hydraulic fracturing when hydraulic fluids and sand are removed from the well shaft. Howarth's bottom-up estimates of leakage rates from a small number of wells range from 1.7-6% for traditional wells, and 3.6-7.9% for shale gas wells, values that include emissions from urban distribution pipelines (Howarth, Santoro et al., 2011).

In August 2012 the EPA enacted new mandates for reducing emissions associated with completing hydraulic fracturing and for additional self-reporting of emissions, infrastructure and production statistics (EPA, 2012). Within a month, an industry group released a report based on a voluntary survey that said liquid unloading emissions were not 22 times larger than the old values as the 2011 report had claimed, but only 1.6 times as large. The official 2013 inventory cited this industry report, significant stakeholder engagement and larger self-reporting through the Greenhouse Gas Reporting Program as motivation for reducing NG-sector methane emissions by 20% and retroactively updating old estimates. The updated estimates do not show any increases in emissions corresponding to the initial fracking boom indicating errors in its data or methodology. The 2013 inventory stated an awareness that peer reviewed studies indicated a need for higher inventory values and requested feedback for integrating that data. "*Finally, Several recent ambient measurement studies (e.g. Petron et al. 2012) have implied higher methane emissions from natural gas systems in certain areas than would be expected based on bottom-up estimates. EPA is aware of such studies and is interested in feedback on how information from atmospheric measurement studies can be used to improve U.S. GHG Inventory estimates.*" (EPA, 2013a) However, the 2014 inventory failed to integrate peer-reviewed datasets and instead reduced methane emissions by an additional 10%. Ironically, this report cited five studies documenting a need for increasing estimates of methane emissions and summarized many suggestions from commenters for incorporating that research (EPA, 2014a). The 2015 inventory did not significantly revise methane emissions estimations and failed to integrate peer-reviewed datasets or follow up on suggestions received in 2014 (EPA, 2015). This prolonged and systematic bias that favors industry self-reporting to scientific peer-reviewed observations and comments is troubling, particularly since it directly opposes their stated intents.

The official 2015 EPA GHG inventory for has a leakage rate of 0.9% for 2011, with a possible range of 0.7-1.1% (EPA, 2015). Miller estimated those values to be 1.3-2.4% in 2008, a significant increase over EPA values (Miller, Wofsy et al., 2013). Kort estimated 2003 values at 1.4-2.5% with a probable value of 1.9% (Kort, Eluszkiewicz et al., 2008). Howarth bottom-up estimates from a small number of wells range from 1.7-6% for traditional wells, and 3.6-7.9% for shale gas wells, values which include distribution emissions (Howarth, Santoro et al., 2011). Allen compiled data from companies that voluntarily allowed them to measure emissions at their facilities and obtained lower emission rates than EPA inventories, this downward trend could be due to selection bias, but does represent what is achievable through current technologies and management practices (Allen, Torres et al., 2013). Allen's findings have recently been called into question due to concerns about sensor malfunctions raised by an inventor of the sensors used in the study (Howard, 2015). Comprehensive atmospheric measurements from areas with active hydraulic fracturing of shale formations for oil and gas production often yield higher values while neglecting emission from transmission, storage and distribution. Pétron estimated pre-transmission emission rates in the range of 2.3 – 7.7% based on 2008 atmospheric methane measurements over active shale fields in Colorado (Pétron, Frost et al., 2012). Schneising used satellite observations to estimate methane emissions at 10.1+-7.3% and 9.1+-6.2% from two high growth regions in the northern and southern US for the years of 2006-2008 and 2009-2011 (Schneising, Burrows et al., 2014). Karion measured leakage rates in the range of of 6.2 - 11.7% over a production field in Utah in one day in February of 2012 using a detector mounted on an airplane (Karion, Sweeney et al., 2013). There is clearly a large degree of uncertainty in our understanding of these emissions and a need for greater clarity.

Emission intensity of fossil generators

To understand the underlying emission tradeoffs of various fossil technologies, it is useful to consider the emission intensity of various fossil generation technologies (Fig A1). Three types of coal technologies are included as reference points: Steam Turbines (ST) that represent older coal generation, Integrated Gasification with Combined Cycle (IGCC) that represent more thermally efficient modern coal generation and IGCC with Carbon Capture and Sequestration (IGCC-CCS) which represent a potential future technology. Three types of NG technologies are considered: Combustion Turbines (CT) that represents "peaking" power plants with low capital costs and relatively poor thermal efficiency, Combined Cycle Gas Turbines (CCGT) that represent more costly and efficient units that could directly replace coal, and CCGT with CCS which represent a potential future technology.

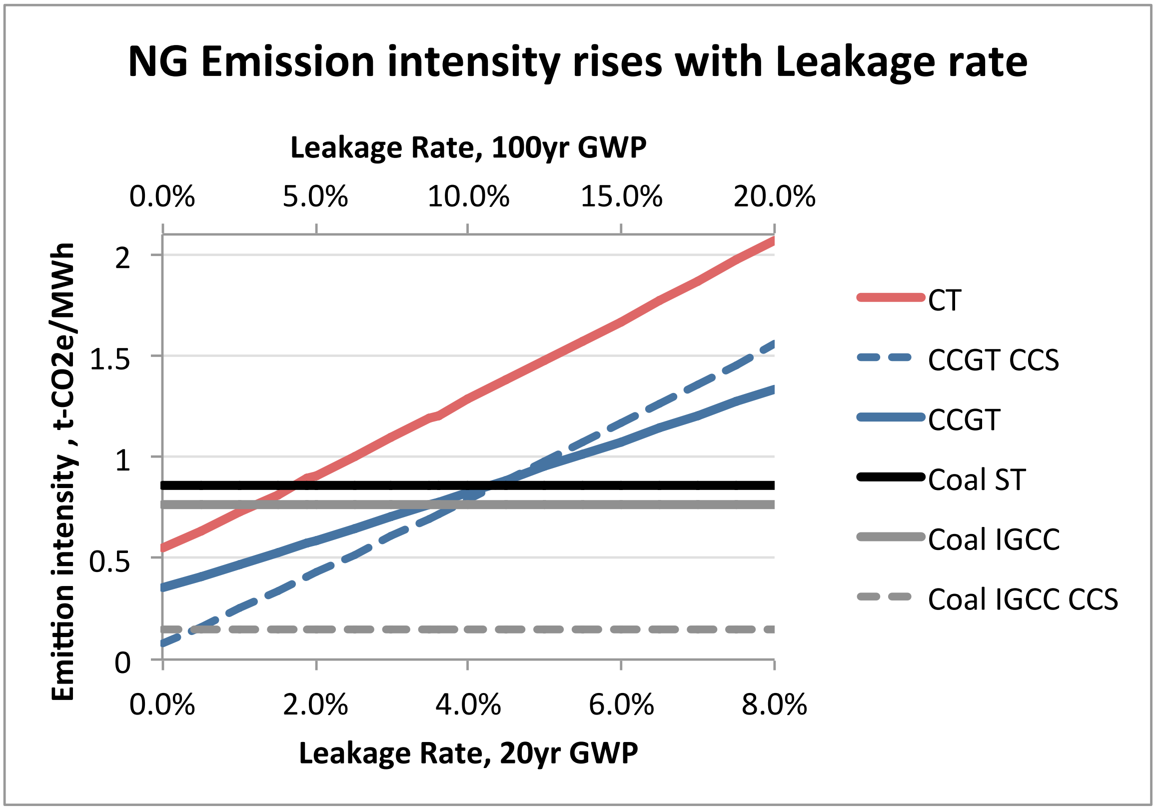


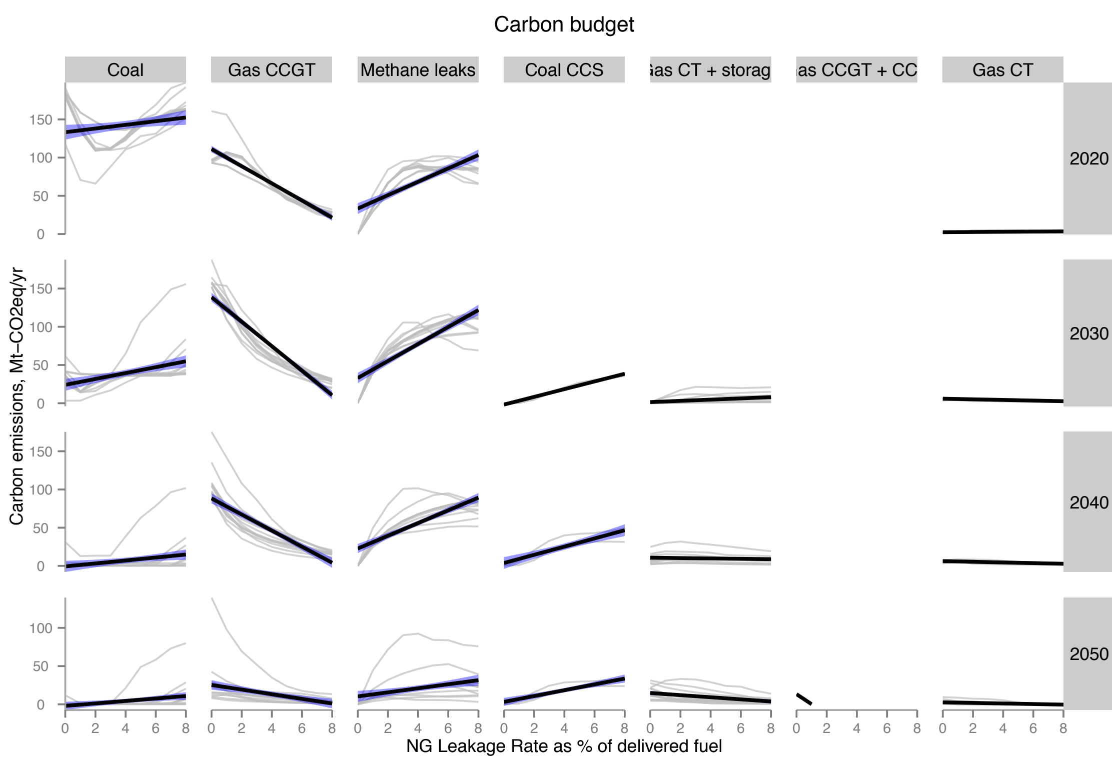
Figure A1 Emission rates of six fossil fuel technologies as a function of natural gas leakage rates illustrate underlying tradeoffs for the direct substitution of coal and natural gas. A secondary x-axis is provided to help visualize the linear relationship in a simple emissions budget between 20-year and 100-year GWP.

At leakage rates less than 4%, CCGT with or without CCS can provide electricity with lower emissions than coal at all examined GWP timescales. This threshold around 4% is consistent with other estimates from literature. The direct emissions benefit of CCS comes with a cost of having to burn more fuel to provide energy for capturing carbon from the smokestack. If leakage surpasses 4%, the upstream CH4 emissions from CCS's additional fuel consumption overwhelm the benefits of reducing smokestack CO2 emissions. Also, CCGT with CCS only has lower emission intensity than Coal IGCC with CCS at very low emission rates. NG CCS has a comparative disadvantage to Coal CCS, due to the lower concentration of CO2 in the exhaust gases. Both CCS technologies were post-combustion amine capture, which has significant energy requirements and an upper limit of 85-90% capture efficiency with diminishing returns at higher capture efficiencies. NG may have better relative performance than coal with other CCS technologies such as pre-combustion water-gas shift capture or combustion in a pure oxygen environment that does not require separating CO2 from atmospheric nitrogen in the exhaust gases. Alternative CCS technologies are not examined in this paper. Methane emissions from coal extraction were also not considered in this study; if included the emission intensity of coal generation would increase, especially for Coal-CCS.

Modeling contribution of Leakage to a carbon cap

In this model, all natural gas consumed by the electricity sector has direct emissions of CO2 and indirect upstream emissions of methane, both of which contribute towards the emissions cap. To convert methane to CO2-e for the emissions cap, we used a factor of 86 based on the 20-year Global Warming Potential from the 2013 IPCC report. The 20-year GWP was more appropriate for this timeframe in order to avoid climatic tipping points such as highly reflective ice melting from the polar regions or massive CO2 and methane releases from decomposing biomass that had been kept stable by permafrost. A 20 year global warming potential served as a simple linear proxy for the complex and non-linear time dynamics of global warming. The linear nature of GWP allow a simple translation between timeframes; to interpret these results in the context of a 100-year GWP of 34, the reader may multiply a given leakage rate by a factor of 2.5. Thus a leakage rate of 2% in a 20-year GWP analysis is equivalent to a leakage rate of 5% in a 100-year GWP analysis.

Carbon Budget Allocations



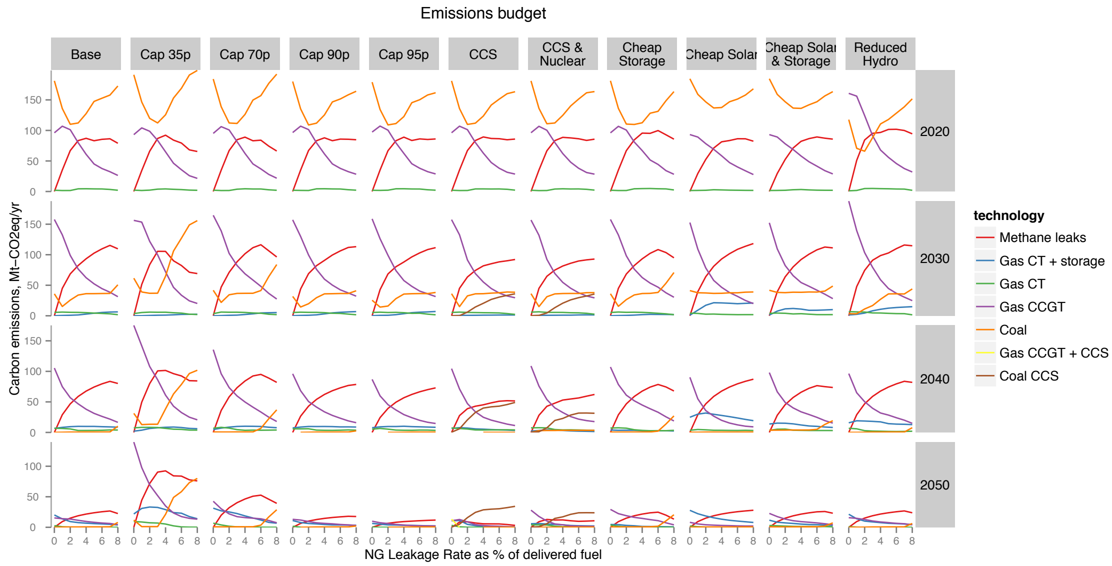


Figure A2 *Top:* Comparison of emission budget allocations by source between scenarios. Source budget for each scenarios shown as grey lines. Central tendency shown as strong black line with blue confidence interval. Scenarios have similar budget breakdowns in most cases. *Bottom:* Comparison of emission budget allocations by source within each scenario. Methane leaks can account for the majority of the emissions budget in 2030-2050 for many scenarios when leakage rates exceed 3-4%.

Materials availability

Summary tables of my results along with R scripts for loading data, running regressions, displaying summary statistics, and drawing a variety of exploratory figures is available at either of these urls:
https://drive.google.com/folderview?id=0B5QpaS5J0GuDfnFSNUNxTk1ac1NDMFNZUDZENnFpMnhQSl94RXFTLVBXSng1YTMwTEJoWlk or
http://rael.berkeley.edu/ng_leakage/ This folder includes 947 exploratory figures from the published results in the `figures` directory, which I found invaluable for performing quality control and for identifying trends in the data worth exploring in a more targeted and quantitative manner. If you wish you explore the results in more detail and are comfortable working with R, I encourage you to use the code I wrote as a starting point for your explorations.

To reproduce statistical analysis and figures, run R scripts inside the directory `ng_leakage` using a recent version of Rstudio after setting the working path to that directory. If you have trouble with understanding the data or using these scripts, email me for assistance: siah@berkeley.edu and I will try to help you on a best-effort basis.

All of my code, model input data and results are available on request. They are too large to readily share on a free cloud service at the moment, plus the model requires proprietary software to run and most people need technical support to set up or use the model, so you might as well email me if you want to run things. I plan to post these on an open and publically accessible scientific archive to coincide with the publication of the paper, so if you are reading this in the future, you can probably find a direct download with an online search. The code is freely available under a GPL license. The data and results are freely available under a Creative Commons Attribution 4.0 International License.

Drivers of Cost Response to Methane Leakage

The Reduced Hydro scenario has the largest increase in costs and decrease in NG consumption in 2020-2030 because under zero leakage, it relies more on CCGT to replace Hydro while it can retire Coal to make room in the carbon budget for CCGT. Reduced Hydro also has the largest cost increase in 2040 because the lack of energy and flexibility from hydro cause it to build relatively larger portions of renewables and accept larger amounts of curtailment. In 2050, Reduced Hydro's cost impacts fall to the middle of the pack, possibly because it was already forced to make infrastructure investments compatible with very low emissions.

The CCS scenario shows the most dramatic increase in cost and decrease in NG consumption in 2050 as leakage increases above 0 as all CCGT+CCS capacity that is deployed under zero leakage is phased out at 1% leakage and replaced with an assortment of renewables, batteries, CCGT and Gas CT + storage. Further increases in leakage prompt a different response as increasing amounts of Coal CCS are brought online, causing Wind, CCGT and Gas CT + storage to decline as Batteries increase and Solar Photovoltaics and Solar Thermal fluctuate up and down with a non-linear response. In both CCS scenarios, Coal CCS is only installed at leakage rates at 2% or above, and is only used in pure baseload mode in 2030. In 2040 and 2050, Coal CCS capacity will ramp down to the range of 40-50% power output during seasons or weeks with more renewable availability to save its emissions budget for higher stress periods. It is worth noting that the methane emissions associated with coal extraction were not considered in this analysis and would decrease the deployment of Coal CCS if they were considered.

The 35% carbon cap scenario shows the largest total decline in NG consumption in 2040-2050 and increase in costs in 2050 because the relatively weak carbon cap permits the largest amounts of NG in both decades relative to other scenarios. Leakage has less impact on that scenario's costs in 2040 relative to 2050 because it has a relatively larger selection of lower-cost options under the weaker carbon cap of 2040. The 70% carbon cap scenario has similar dynamics and shows the next-largest responses in those timeframes.

The 95% carbon cap scenario shows the least response in costs and consumption in 2050 because it has very low dependence on NG due to the tight carbon cap. The 90% carbon cap scenario shows a similar low response to consumption but a relatively higher response to cost, suggesting a threshold in the transition to low emission grids over which NG becomes less valuable. The availability of alternatives to gas also plays a role in mitigating cost impacts. The cheap solar scenario has some of the lowest cost responsiveness to leakage rate in 2020-2030 while the carbon cap allows enough sufficient natural gas at all leakage rates so that system flexibility is not a major driver of cost. Similarly, the Cheap Solar & Storage scenario has the lowest cost responses in 2020-2040 and the third-lowest cost responses in 2050. Under the relatively tight carbon caps of 2040-2050, the CCS & Nuclear scenario has the second lowest cost responsiveness as the system gradually becomes dominated by Nuclear power in the 2040 and 2050 timeframes.